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Performance prediction of individual lead-acid cells in long strings

Xiang Li
San Jose State University

PERFORMANCE PREDICTION OF INDIVIDUAL LEAD-ACID CELLS IN LONG STRINGS

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Xiang Li

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APPROVED FOR THE DEPARTMENT OF CHEMISTRY

Dr. Sam P. Perone

Dr. Joseph J. Pesek

Dr. Karen Singmaster

APPROVED FOR THE UNIVERSITY

ABSTRACT

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by Xiang Li

This work explored for the first time the use of both battery maintenance data and fabrication data for the prediction of individual lead/acid cell performance in a large energy storage battery, as measured by individual cell capacity values. Computerized pattern recognition was used to determine which measurements taken during fabrication and maintenance were most useful for accurate prediction of individual cell performance. Prediction accuracy of almost 90% could be achieved with selected data features. Thus, we conclude that the combined maintenance and fabrication database contains the information content necessary for accurate prediction of individual cell performance.

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INTRODUCTION

1.1. Description of the Battery System

This project began in June, 1983, with the production of 340 (2080 Amp-hour, Ah) large lead/acid cells by GNB. Inc. for the Electric Power Research Institute (EPRI), located in Kankakee, Illinois [1]. The basic requirement of battery performance was to deliver 500 kW for 1 hour. At this rate the cell capacity limit was set at 1040 Ah. For a 5-h discharge at the 2080 Ah cell capacity, 1.2 MWh of stored energy could be delivered. The battery was guaranteed for 8 years.

Fabrication materials and measurements were recorded in detail for each numbered cell by GNB and the cells were produced and tested in four batches of 80 cells each, and a fifth batch of 20 cells. These 5 batches were labeled "circuits" 1 to 5. 324 (fifty-four 6-cell modules) out of 340 cells were installed at the Battery Energy Storage Test (BEST) Facility in Newark, NJ, operated by Public Service Electric and Gas Co., and acceptance tests were completed on December 7, 1983. Over 200 cycles of tests were performed at the BEST Facility from 1983 to 1987. In July of 1987, the battery was conveyed to and installed at Crescent Electric Membership Corporation (CEMC), Stateville, North Carolina, an area electric power distributor. Since then, the battery has operated as a peak-shaving device, to discharge at a maximum power of 500 kW for 1 hour and at a minimum power of 200 kW for 3 hours. Battery maintenance data have been collected quarterly at CEMC. In addition, capacity tests were performed at CEMC in March, 1989 and April, 1990 for a carefully selected subset of 109 to 121 cells. A full capacity test for all cells was performed at CEMC in September, 1991. Prior to July, 1991, only one cell (#241) had been removed due to low capacity.

Studies on each stage of the battery's life have been published [2-4] using statistical, pattern recognition, and cluster analysis. There were three stages of the battery life : after initial fabrication and testing; after cycle testing at BEST, and after several years of operation at CEMC. Results of these studies showed that information required for cell performance prediction exists in initial fabrication data and in operating maintenance data; however, prediction accuracy was not high enough for practical application. The study of fabrication data resulted in maximum prediction accuracy of ~ 48%. For the maintenance data study, about 57% overall prediction accuracy was obtained.

The study reported here extends the previous works by examining the combined the maintenance data and fabrication data to determine if subsequent cell performance could be predicted more accurately. In addition, this work examines for the first time the use of class-weighted training as a pattern recognition technique to achieve high accuracy prediction of selected classes.

This work is concluded with prediction performance of individual cells in big energy storage systems involving strings of 100's or 1000's of cells. The ability to distinguish high and low performing (high/low capacity values) cells is important for allowing preselection of good cells (high capacity values) and exclusion of poor cells prior to cell failure. Cell failure can cause serious, sometimes disastrous damage to battery strings; hence, if problem cells can be identified and replaced prior to cell failure, battery energy storage systems can be operated more effectively and safely. Our work intends to demonstrate how fabrication data and maintenance data could provide this ability through computerized pattern recognition. If successful, this strategy might substitute for periodic cell capacity tests, or provide early indication of imminent cell failure in large battery installations where expensive capacity tests are not practical.

1.2. Battery Description and Background

The lead/acid cells used for this work consist of negative and positive electrodes which are made of sponge lead and lead peroxide, respectively, and are immersed in sulfuric acid electrolyte [5]. (Figure 1a). A typical lead/acid cell can be represented by:

$$Pb\ (s) \,|\, PbSO_4\ (s) \,|\, H_2SO_4\ (aq) \,|\, PbSO_4\ (s),\ PbO_2\ (s) \,|\, Pb\ (s)$$

and the reactions are:

$$Pb\ (s) + SO_4^{2-}\ (aq) \rightarrow PbSO_4(s) + 2e^- \qquad \text{Negative Electrode}$$

$$PbO_2(s) + 4H^+\ (aq) + SO_4^{2-}\ (aq) + 2e^- \rightarrow PbSO_4(s) + 2H_2O \qquad \text{Positive Electrode}$$

$$Pb\ (s) + PbO_2(s) + 2H_2SO_4(aq) \rightarrow 2PbSO_4(s) + 2H_2O \qquad \text{Cell Reaction}$$

where the first two reactions are half-cell reactions and the last one is the cell reaction.

The material used in the negative electrode is sponge lead which is porous and allows the electrolyte to penetrate [6]. This results in maximum cell efficiency [6]. The so-called electrochemical storage cells do not actually store electrical energy; they directly convert electrical energy into chemical energy during charging. When a load is connected on the charged cell, the stored chemical energy is converted back into electrical energy.

When a cell is discharged, the two electrodes react with the electrolyte -- sulfuric acid and form a coating of lead sulfate (Figure 1b). Meanwhile, the sulfuric acid is consumed and the specific gravity of the electrolyte decreases and so does the cell voltage. In a completely charged state, the cell voltage is at a maximum of slightly greater than 2 volts (2.06 V); the specific gravity is at the highest state too, between 1.200 and 1.290. When a cell voltage drops below about 1.7 V during discharge, cells are not discharged further because the electrodes (Figure 1c) will suffer irreversible damage [6].

When a cell is charged, the lead sulfate coated electrodes react with water to produce sulfuric acid, and each electrode returns to its original state. During charging, the cell voltage, along with specific gravity, gradually increase back to their maximum state.

The total charge that a cell can provide before reaching the cut-off voltage (typically 1.7 V) is called "capacity." This quantity (Ah) is often expressed as a percentage of the nominal or designate capacity. This characteristic does not depend on the number of cells in series, but depends on the size or number of plates in a cell. However, the number of cells can affect the cell voltage. If cells are connected in series, the total voltage is equal to the sum of each cell voltage. Hence, for large power application several cells formed in series constitute a battery. Storage batteries also serve other functions [6]: e.g., voltage stabilization, preventing frequency fluctuations, and reserve energy source for emergencies.

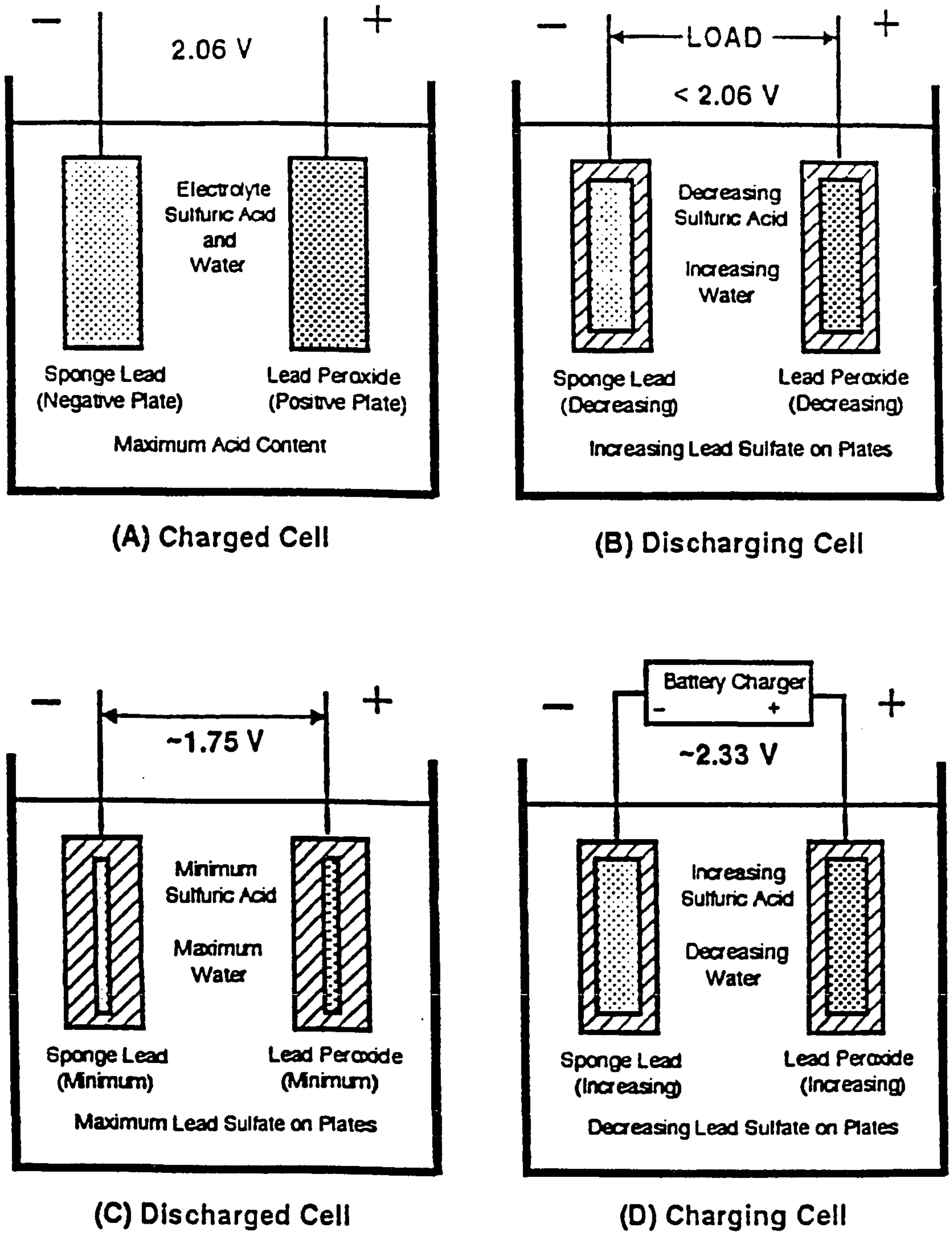


Figure 1. Physical chemical states of a typical lead-acid cell.

1.3. Pattern Recognition Techniques

Pattern recognition involves the perception of regularities among sets of data describing objects or events. It is concerned with processing large amounts of data, the selection of useful descriptors which contain the most information, and the classification of the objects by examining those descriptors.

A pattern can be simply defined as a d-dimensional vector composed of d independent measurements, and can be expressed as:

$$P_i = w_1 x_{1i} + w_2 x_{2i} + w_3 x_{3i} + \ldots + w_d x_{di} + w_{d+1} \quad (1)$$

in which x_{1i}, x_{2i}, x_{3i} ......are components (measurements) of the pattern vector for the ith sample, $w_1, w_2, w_3, \ldots\ldots w_{d+1}$ are components of weight vector, and d is the number of dimensions.

Because the raw data may define a large dimensional vector, a reduction of dimensionality is often needed in order to obtain reliable classification. That is, N features may be selected from the raw data which contain the best characteristic to distinguish properties of each class (where $N <$ d). These features may be raw data, combinations or transformations of the raw data. To select the most information from these features, numerous systematic techniques have been applied, e.g., correlation analysis, statistical distribution analysis, and empirical methods such as sequential iterative feature elimination [7-16].

1.3.1. K-Nearest Neighbor Analysis

In this work, one of the pattern recognition techniques used is the *K*-Nearest Neighbor (KNN) classification. For the KNN method, the class of an unknown item is predicted from the majority class of its *K* nearest neighbors in *N* - dimensional feature space. *K* is commonly a small odd integer, usually one. In order to get nearest neighbors, the inter-item distances in feature space need to be calculated. Euclidian geometry is used for this calculation, where:

$$D_{ij} = \left[\sum_{n=1}^{N} (X_{in} - X_{jn})^2 \right]^{1/2} \qquad (2)$$

in which i, j are specific items, n is the index for all features, and N is the total number of features. Comparing all calculated distances, the unknown item is then classified as the same as the majority of its *K* nearest neighbors, as illustrated in Figure 2 [14-16].

One of the main advantages of this method is that it can be applied not only to non-linear classification problems but also to multi-class identification problems. However, there are some disadvantages. First, classification of each unknown item requires examination of all patterns for *K* nearest neighbors. This esults in long compute time. Secondly, this method can not tell which features are more useful than others. Nevertheless, the KNN method has been successfully used in a variety of applications, such as classification of mineral waters from different regions[17], classification of electrochemical processes [13, 18-20], prediction of battery lifetime [3], etc.

1.3.2. Non-Linear Mapping

Since it is difficult to visualize features when feature space dimensions are larger than 3, several mapping techniques have been applied to reduce the multiple feature spaces to two dimensions. The Non-Linear Mapping (NLM) method [21,22] was found to be the most useful for our work.

The NLM method involves transforming data in N- dimensional feature space into 2- dimensions, while trying to keep the relative inter-item distances which exist in N-space. This is done by minimizing the mapping error, that is:

$$E = [\sum d_{ij}]^{-1} [\sum (d_{ij} - d_{ij}^{*})^2 / d_{ij}] \qquad (3)$$

in which d_{ij} is the interpoint distance in N-dimensional measurement space and d_{ij}^{*} the interpoint distance in 2-space. The procedure of non-linear mapping requires large numbers of calculations, and usually takes a large amount of a computer time.

Thus, the NLM method becomes much more effective when an initial selection of a small set of useful features is performed. Prior feature selection (correlation analysis, univariate discriminating power [10, 23, 24], and sequential feature elimination [25], etc.) leads to a smaller data matrix, and faster execution time.

1.3.3. Correlation Analysis

Correlation analysis involves calculating the linear correlation coefficient for each pair of features in a multivariate data matrix. The Pearson correlation coefficient is defined as:

$$R_{a,b} = \{X_{ia} - \overline{X}_a)\cdot(X_{ib} - \overline{X}_b)]\} / (X_{ia} - \overline{X}_a)^2 \cdot (X_{ib} - \overline{X}_b)^2]^{1/2} \qquad (4)$$

here X_{ia}, X_{ib} are feature values of a and b for item i, and $\overline{X}_a$, $\overline{X}_b$ are the mean values of features a and b. $R_{a,b}$ is between +1 and -1. When R is equal to zero, there is no relation between set A and set B. On the other hand, when the absolute value of R is closer to 1, there is a high correlation, and one or the other of the feature pair can sometimes be eliminated from the feature set (see below).

1.3.4. Sequential Feature Elimination

Sequential feature elimination involves the arbitrary deletion of a feature after a given feature set is evaluated for classification accuracy. If elimination of the feature results in a drop in the overall classification accuracy with subsequent pattern recognition analysis, the feature is added back into the feature set. The feature will be remain out of the feature set when the classification accuracy is not decreased or is improved by removing the feature. This procedure is continued until no further deletions are allowed, and the maximum classification accuracy is achieved with a minimum of features. The order in which the features are examined can change the outcome of the results. The subject of sequential feature analysis has been treated in detail [25].

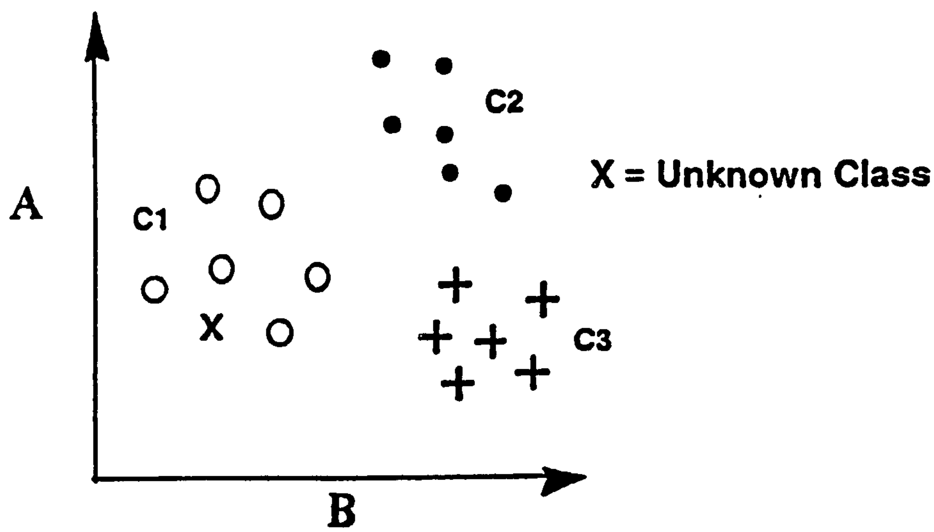


Figure 2. Nearest neighbor analysis in two dimensions.C1, C2, C3 represent clusters of three different classes of items each characterized by two measured features, A and B. Item X is of unknown class.

1.4. Aims of Work

The goal of this project is to search for multivariate relationships among fabrication, maintenance and capacity data obtained at different stages of the lifetime of the lead/acid cells used in deep-cycling energy-storage applications; to evaluate correlation of fabrication and maintenance data with cell performance and lifetime; and to predict individual cell performance, as measured by individual capacity values. The objectives are to determine if fabrication and maintenance measurements can be used to predict cell performance; to illustrate which measurements contain information content necessary for accurate prediction of cell performance; and to gain insight to chemical and physical processes underlying electrochemical cells which affect cell performance and lifetime.

The study described here is based on two previous studies of our research group: lead/acid cell performance prediction from fabrication data and from maintenance data respectively [4, 26]. The maintenance data study showed that the index used to order the maintenance data was crucial to obtaining useful features for pattern recognition. The best results were obtained when the index was based on battery activity, as determined by the amount of water addition. Although both previous studies demonstrated that known cell performance could be correlated with either data set, neither provided an adequate basis for the prediction of future cell performance. The work reported here attempted to improve the cell performance prediction by examining both data sets and by using class-weighted recognition principles. The basic approach involves using computerized pattern recognition techniques [7-11]. These techniques were evaluated previously by Byers and

Perone [27] for lifetime prediction of individual sealed Ni/Cd cells tested at the Crane Naval Weapons Support Center; based on multivariate analysis of the manufacturer's fabrication and initial test data. Later [3], the usefulness of pattern recognition was verified by studying initial test data and the lifetime for individual lead/acid cells.

Chapter 2

EXPERIMENTAL

2.1. Instrumentation, Database and Software

An IBM/PC clone personal computer was used for all database management and pattern recognition studies. The minimum configuration used included 8 MByte RAM and a 250 MByte hard disk, with a 33 MHz 386 microprocessor.

All data are contained in a SYMPHONY™ database management system. SYMPHONY™ was used to perform all statistical computations (averages, variances, distributions, standard deviations, etc.) and associated graphical procedures. Pattern recognition software programs were written "in house" using a compiled BASIC programming language and were used to perform all multivariate analysis procedures (pattern recognition, correlation analysis, and non-linear mapping).

2.2. Basic Procedures

2.2.1. Database Information

The raw database used for this study contained all fabrication data (e.g., cell voltages, weight of materials, electrolyte charge, initial capacity values, etc.) for 324 cells and all maintenance data (float voltages, specific gravities, water additions, and electrolyte levels) collected quarterly for all operating cells between August, 1987 and September, 1991 (subsequent maintenance data have been collected, but were not used for this study, as no further capacity data has been obtained to-date.) Descriptive data patterns were defined for a set of 108 cells which were consistently tested for capacity in 1989, 1990 and 1991. Of these, a sub-set of 42 to 50 cells were used for pattern recognition studies, so that approximately equal numbers of 3 different cell classes could be used. The same set of 42 cells were included in the 1989, 1990 and 1991 data bases, although the classes of individual cells might change due to performance changes. An additional 8 cells were included in the 1991 data base, because all 323 cells were capacity-tested in 1991, and more examples of the smaller classes were observed. The data used for pattern recognition consisted of 9 useful maintenance features collected for each cell in 1989, 1990 and 1991, and 13 useful fabrication features obtained for each cell in 1983. These features were those that had been shown previously to be correlated with individual cell performance [4, 26]. Features used for pattern recognition studies can be the initial measurements (raw data) as well as transformations or combinations of the raw data.

2.2.2. Data Preprocessing

Multivariate data measurements are usually presented as a data matrix (Figure 3) where each row represents samples and each column represents measurements for each sample. Preprocessing of raw data is necessary [28], as multivariate data can hardly be analyzed in this original state, and it eliminates non-inherent artificial properties. One of the procedures to transform data is normalization. The purpose of normalization is to remove the variance in a data set due to incidental differences in magnitudes of different features. Normalized data can be expressed as:

$$(XN_j)_i = (X_j)_i / \overline{X}_j \qquad (5)$$ or

$$(XN_j)_i = [(X_j)_i-(X_j)_{min}]/R \qquad (6)$$

In equation (5), $(XN_j)_i$ is the normalized data value for the jth feature, ith cell of a specific event, $(X_j)_i$ is the raw data value, and $\overline{X}_j$ is the average value of jth feature over all cells of a specific event. In equation (6), R is the range of a set of measurements, and $(X_j)_{min}$ is the minimum value for the jth feature. Either of these methods, or others, may be used to express normalized data, depending on what properties are to be emphasized or de-emphasized. For example, equation 5 provides normalized data which retain relative differences in ranges, but eliminate the differences in magnitudes. Equation 6 eliminates differences in range and magnitudes.

The most commonly used normalization procedure is the "autoscaling" method which can be expressed as:

$$(XS_j)_i=[(X_j)_i - \overline{X}_j)]/(SD)_j \qquad (7)$$

where $(XS_j)_i$ is the autoscaled value for the jth feature, ith cell for a specific event, $(X_j)_i$, $\overline{X}_j$ defined as above in equation (5), and $(SD)_j$ is the standard deviation for the jth feature over all cells for a specific event. Autoscaling sometimes is called "standardization" since it normalizes each feature in a data set to produce a mean value of zero and a SD of unity.

In this work, all pattern features were autoscaled before pattern recognition analysis; therefore, data sets obtained in different time periods can be compared and combined.

$$
\begin{array}{cc}
 & \text{FEATURES OR VARIABLES} \\
 & \begin{array}{cccccc} 1 & 2 & 3 & \bullet & \bullet & c \end{array} \\
\text{ITEMS OR EXPERIMENTS} \quad \begin{array}{c} 1 \\ 2 \\ 3 \\ \bullet \\ \bullet \\ r \end{array} &
\begin{bmatrix}
X_{11} & X_{12} & X_{13} & \bullet & \bullet & X_{1c} \\
X_{21} & \bullet & \bullet & \bullet & \bullet & \bullet \\
X_{31} & \bullet & \bullet & \bullet & \bullet & \bullet \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
X_{r1} & \bullet & \bullet & \bullet & \bullet & X_{rc}
\end{bmatrix}
\end{array}
$$

Figure 3. Graphical representation of a multivariate data matrix. Rows represent individual items or experiments. Individual features or variables are presented in columns for each item.

2.2.3. Defining Class Boundaries

In this study, each cell is assigned to one of three classes which are defined in the following way:

Class 1 : capacity value > (AVG. +1 SD)

Class 2 : capacity value < (AVG. - 1 SD)

Class 3 : capacity values within (AVG. $\pm$ 1 SD)

Thus, class 1 cells have the best performing because of high capacity values; whereas class 2 cells have poor performing due to low capacity values. The measured capacity values are expressed as a percentage of the nominal capacity value (2080 Ah). The classes of individual cells were determined from capacity test data taken in 1989, 1990 and 1991.

In 1989, the average capacity for 109 cells (measured March, 1989) was 95.0% and the SD was $\pm$ 3.1%. Using the above class definitions, the 1989 individual cell classes were:

Class 1: capacities > 98.1% (20 cells)

Class 2: capacities < 91.9% (6 cells)

Class 3: capacities $\geq$ 91.9%, but $\leq$ 98.1% (83 cells).

Figure 4 shows a distribution of the 1989 capacity data. On the graph, capacity values have been rounded off when cells are assigned to a particular capacity value. For example, cells labeled with a capacity of 100% represents capacity values between 99.5% to 100.4%.

For the 1990 capacity test, the average value for 121 cells (measured April, 1990) was 101.5%, and the standard deviation was ± 2.8%. Using the above definitions, the 1990 individual cell classes were:

Class 1: capacities > 104.3% (16 cells)

Class 2: capacities < 98.7% (23 cells)

Class 3: capacities ≥ 98.7%, but ≤ 104.3% (82 cells)

Figure 5 shows a distribution of the 1990 capacity data. The capacity values have been rounded in the same way as in Figure 4.

For the 1991 capacity test, obtained in September, 1991, the average value for 323 cells was 101.5% and the SD was ±3.9%. So the class assignments in 1991 were:

Class 1: capacities >105.4% (35 cells)

Class 2: capacities < 97.6% (48 cells)

Class 3: capacities ≥ 97.6% but ≤ 105.4% (240 cells)

Figure 6 shows a distribution of the 1991 capacity data. The value of 102% represents capacities value which range from 101.5% to 103.4%.

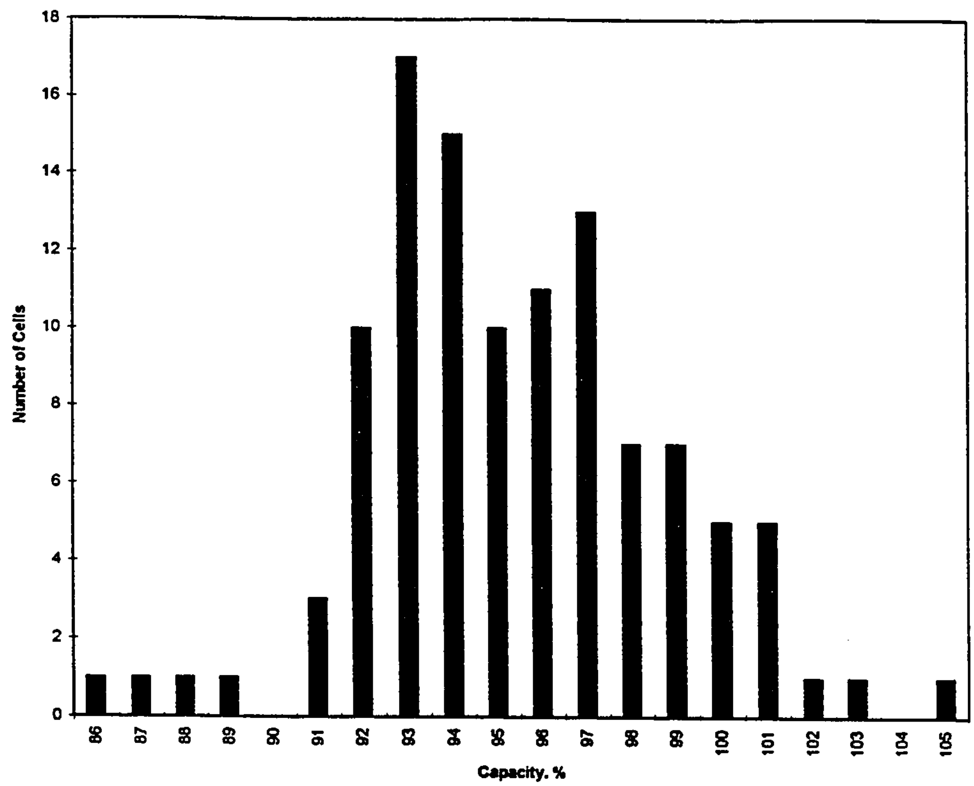


Figure 4. Distribution of cell capacity data collected by CEMC in April, 1989 [2].

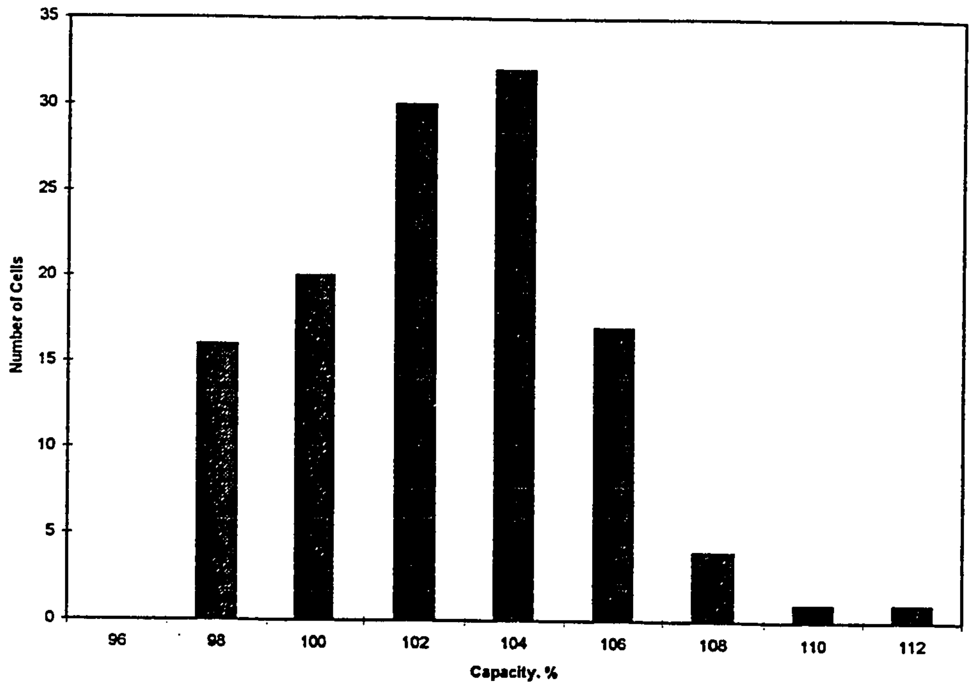


Figure 5. Distribution of cell capacity data collected by CEMC in March..1990 [2].

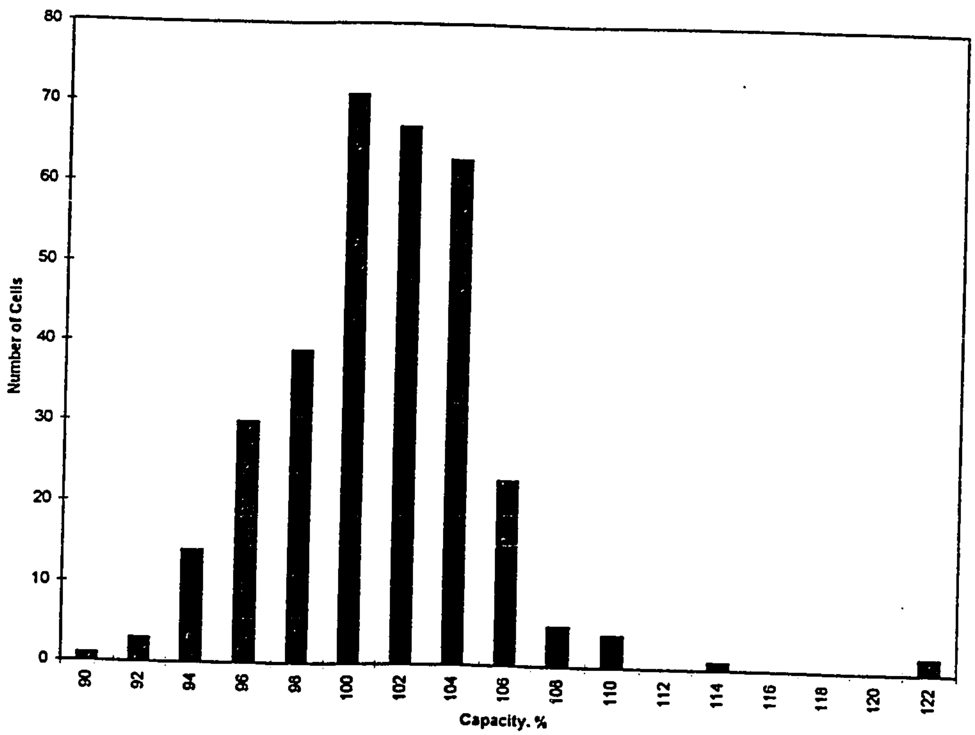


Figure 6. Distribution of cell capacity data collected by CEMC in September. 1991.

2.2.4.Training

After the preprocessing step, the training procedure is usually the next step in the pattern recognition process. Training involves analyzing a training set (where each pattern has a known class) to develop a classifier which recognizes the class membership of each pattern as well as possible. The training procedure includes the LOO-KNN (leave-one-out k-nearest neighbor) classification algorithm [29]. During the training, a pattern is "left out" of the training set and classified using KNN as if it were an "unknown." Then the class of the pattern classified by KNN is compared with the known true class of the pattern. If they are the same, the pattern is classified correctly by KNN. This procedure is repeated for all patterns in the training set and the classification accuracy is determined.

Improvement in the classification accuracy is achieved by selecting alternative sets of features to define the patterns. In our work, this is done with a systematic iterative feature elimination procedure [7-13]. The algorithm allows the user to choose forward or backward feature elimination and whether or not to optimize the feature weights. The forward feature elimination refers to the elimination of features from lowest to highest index numbers, whereas backward elimination proceeds from highest to lowest. The computer speed, the numbers of patterns and features, and the feature weighting option, affect the time of the entire process. The feature weights are usually selected as "1" for preliminary training, where most of the feature elimination is accomplished. When a set of superior classifiers is obtained, feature weights are then optimized. This minimizes the computer time required for the overall training process. Although the truly optimum set of classifiers can only be obtained by considering all possible combination of features in sets of 1 to 22 [7], this would be unacceptably time-consuming. Thus, our approach involves the systematic selection of several different sets of no more than 15 features at a time to initiate separate training/feature elimination procedures.

Consistently useful features are then condensed into smaller sub-sets for further training. Because maximum classification accuracy does not necessarily mean optimum class separation in feature space, several of the better (more accurate) feature sets are retained for further study (mapping and prediction see below).

2.2.5. Classification Accuracy

Classification accuracy can be expressed in several ways. Ws have used two. One is called overall classification A:

$$A = (P / P_t) \times 100\% \qquad (8)$$

where P_t is the total number of patterns in the set and P is the number of patterns classified correctly in the set. The other is called class-specific accuracy A_c:

$$A_c = (P_c / P_m) \times 100\% \qquad (9)$$

where P_m is the total number of patterns in class m and P_c is the number of patterns classified correctly in class m. If classification accuracy is low, then different measurements or alternative data transformations and combinations should be investigated in order to achieve high accuracy.

2.2.6. Mapping

After training, some feature groups provide high classification accuracy, but the results may be fortuitous, and therefore the feature groups are not valid. The NLM method (described in section 1.2.2.) is a useful, independent measure of classifier effectiveness because it transforms data from N-dimensional feature space into two dimensions and allows visual "pattern recognition." Visual examination of mappings can determine whether or not pattern vectors for different classes are clustered separately in feature space. If not, high accuracy KNN-classification is likely to be fortuitous, and the particular feature set might be eliminated from further study. Another use of NLM is to observe the items consistently found within a cluster of patterns which belong to a different class. In earlier work [2, 4], it was found to be useful to re-classify these items based on the clusters they are in, and perform the training procedure again. Usually, different feature sets will be selected when re-training a pattern-reclassified training set. Often, a higher classification accuracy is obtained compared with early results. More importantly, the disruptive effect on the training process due to the anomalous cells is eliminated, and more meaningful pattern classifiers are obtained for prediction studies (see below).

2.2.7. Prediction

When classifiers of sufficient accuracy are obtained from the training procedures, the reliability of each can be evaluated by classifying a different set of known patterns called a prediction set. Patterns in the prediction set have the same origins as the training set, and represent the same classes included in the training set, but are not part of the training set. For example, in this work a training set patterns might be obtained by combing fabrication data with 1989 maintenance data, whereas the prediction set used to evaluate the validity of selected features could be obtained from combing fabrication data with 1990 maintenance data.

Classification accuracies of the prediction set are also calculated using equations 8 and 9. If the prediction accuracy is high, the classifiers from the training set study are probably valid and reliable, and they can be applied to a true unknown set. Unknown sets contain patterns with the same measured parameters as the training and prediction sets, and the same classes of measured items, but the actual class information is not available. Prediction procedures are performed not only for training set features but also for features obtained from pattern reclassified training.

2.2.8. Class-Weighted Training

The purpose of class-weighted training is to evaluate class-specific classification accuracy independently for class 1 and class 2 cells. Training procedure was used for previous work where the overall accuracy was the criterion for feature selection; however, for this project, training was also conducted where the class 1 and class 2 classification accuracies were used independently as the guiding figure of merit. Because the class 1 cells have high performance (high capacity values), if their classification accuracy is high, the preselection of superior cells might be achieved even with moderate overall accuracy. On the other hand, if class 2 classification accuracy is high, then most or all potentially problematic cells can be identified and replaced prior to cell failure. In addition to achieving high class-specific accuracy, it is also important to consider the number and nature of "false positives." For example, to preselect a set of high capacity cells, classifiers should provide high class 1 accuracy with few or no "false positives." Moreover, false positives from class 3 cells are preferred to class 2. For recognition of class 2 cells, however, false positives may be more acceptable as long as most problem cells are identified. Feature elimination and feature weight optimization use a weighted classification error factor as a figure of merit. The error is obtained from equation 10.

$$\text{Error} = [\text{Total \# wrong}] + [\text{\# wrong weighted class items}] + [\text{\# false positives of weighted class}] \qquad (10)$$

Non-linear mapping is also applied to features obtained from class-weighted training, just as described previously, except that only the isolation of either class 1 or class 2 items is evaluated regardless of the overlap of the other two classes. Re-classification of anomalous cells based on NLM results can be also conducted as described previously, except only the selected class is evaluated. Prediction studies are again conducted just as described previously, except the performance is based on the selected class.

Chapter 3

RESULTS AND DISCUSSION

Earlier pattern recognition studies of battery test data have been published [3, 27] and work with the GNB battery system has also been reported [1, 30-32]. The earlier reports [3, 27] described multivariate analysis of lead-acid and nickel-cadmium battery test data and initial attempts at battery lifetime prediction from manufacturer's fabrication/test data. Reference [1] contained a summary of all fabrication/test data for the GNB lead-acid cells studied in this work. Reference [30] examined the GNB fabrication/test data for inherent clusters of cells with common multivariate properties. References [31, 32] examined performances of individual cells during the battery system operation at BEST Facility and at CEMC, and also examined continued correlations with initial fabrication parameters. Reference [33] observed the battery system as it entered its final phase of operations at CEMC, and evaluated performance prediction from routine maintenance data. Reference [4] evaluated GNB fabrication data for prediction of cell performance as the battery entered its final phase of operation at CEMC. The work reported here will determine which feature sets from the combined fabrication and maintenance features might provide improved classification accuracy.

3.1. Manufacturer's Fabrication /Test Data

Some useful features (descriptors) extracted from the initial data base for statistical and multivariate data analysis are summarized in Table 1. Temperature data were also collected for correcting specific gravities and capacities to standard conditions (77°F).

Results showed that among the five formative batches (circuits 1-5) statistically significant differences existed for the mean values of 80% of the measured variables [26, 27].

Multivariate cluster analysis with various combinations of fabrication/test features [2] showed that cells in circuits 1 and 3 were distributed into two distinct subsets. Figure 7, for example, illustrates the distinct clustering observed in a seven-dimensional feature space for circuit 3 cells. This observed clustering could be associated with manufacturer's documentation, specifying which grids or pasted plates were fabricated from "old" or "new" stock materials. Table 2 summarizes known material changes during fabrication of GNB cells. All batches of materials met procurement specifications for chemical and physical characteristics. Thus, the occurrence of distinct subsets of cells, reflecting distinctly different multivariate properties, was not expected to be associated with changes in the fabrication materials. Cells in circuits 2 and 4 had no known changes in fabrication materials or procedures, but distinct cell sets were also observed with multivariate cluster analysis [2]. Figure 8 illustrates the clustering observed in a six-dimensional feature space for circuit 2 cells. Examination of fabrication procedures showed that the different clustered sets of cells could be associated with physical placement of those cells during formation cycles.

Table 1

Useful features (descriptors) from factory data base.

Features	Definition
ASHPA	final acid adjustment before shipping
AVCAP	average capacity over 5 test cycles
AVSA, AVSB	average SGA, SGB over 5 test cycles
CAPSLFA	total acid in cell before 5th test cycle
DRYWT	cell weight before acid addition
EQWC	acid added (equalization) before 5th cycle
EQWF	acid added in formation equalization step
FINLWT	total weight of cell after formation equalization
INDL	AVCAP/RNGCAP
MNCAP, MXCAP	minimum/maximum capacity of 5 test cycles
MNSA, MXSA	minimum/maximum SGA over 5 test cycles
RELFRMA	EQWF/(FINLWT-DRYWT)
RNGCAP	(MXCAP-MNCAP)
RNGSA	(MXSA-MNSA)
SGA, SGB	specific gravity after/before discharge each cycle
SG2	specific gravity prior to formation equalization
SG4	specific gravity prior to 5th cycle equalization
SHPSLFA	total acid in cell as shipped

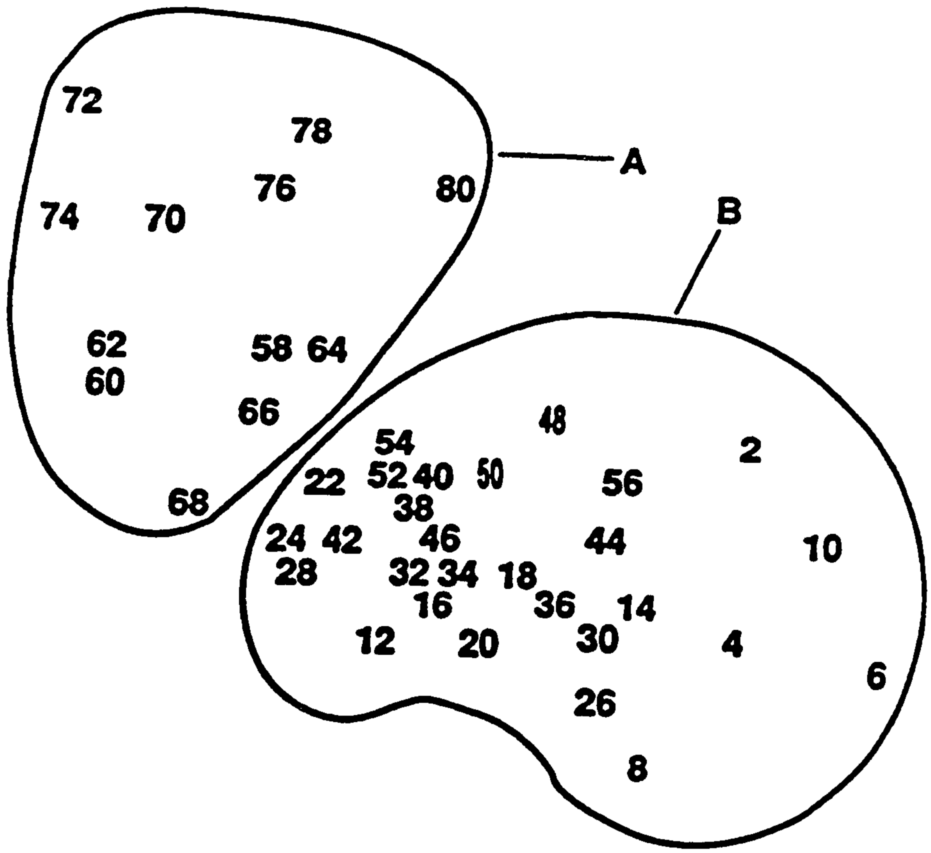


Figure 7. Non-linear mapping (NLM) of seven-dimensional feature space for fabrication/test data, GNB cells, circuit 3 only. Mapping data for even-numbered cells (162-240), identified as 2-80. A=new/new grid/paste; B=old/new grid/paste. Features: DRYWT, EQWF, MXCAP, MNCAP, AVCAP, MXSA, RNSGA [2].

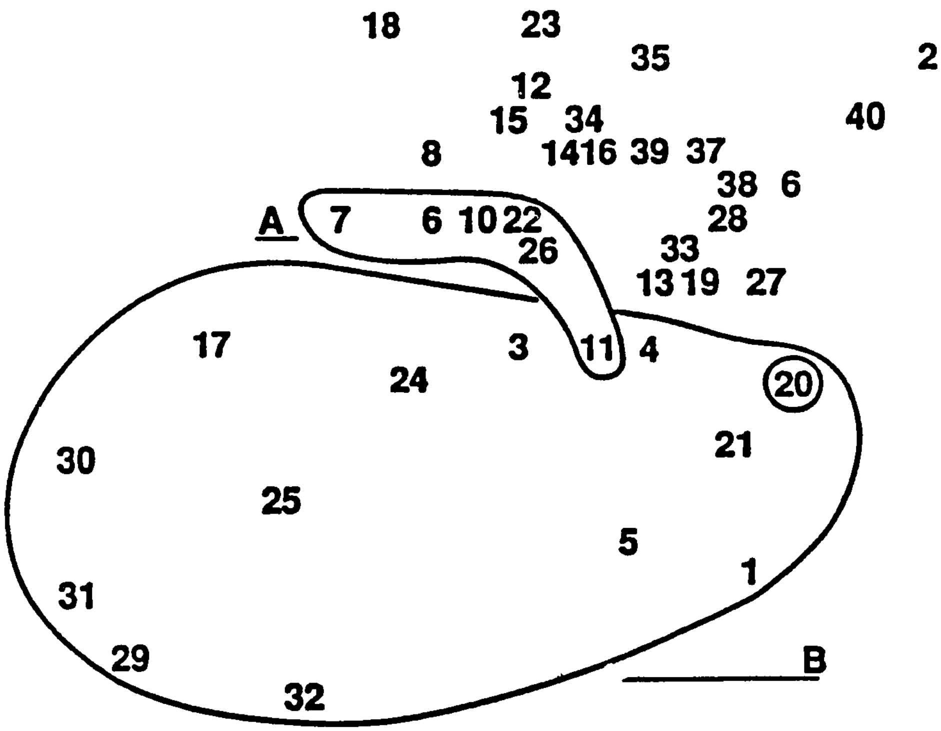


Figure 8. Non-linear mapping (NLM) of six-dimensional feature space for fabrication/test data, GNB cells, circuit 2 only. Mapping data for cells 80-120, identified as 1-40. A= interior cells; B= exterior cells. Features: SG2, EQWF, MNCAP, AVCAP, AVSA, RNSGA.

Table 2

Summary of materials changes for GNB cells.

Subset	Circuit	Cells	Grid	Pasted Plate
(a)	1	1-15	old	old
(b)	1	16-80	old	new
(c)	3	161-218	old	new
(d)	3	219-240	new	new

3.2. Data from BEST Cycle Testing

Battery maintenance data (electrolyte levels, water additions, specific gravities, cell float voltage.) were collected quarterly at the BEST Facility from 1983 to 1987. A full capacity test was performed in January, 1986.

Multivariate cluster analysis was applied to the BEST capacity test data [3], using features selected from the data descriptors defined in Table 3. Table 4 summarizes the results of the various cell subsets in the CEMC capacity tests. Groups G1-G4 were observed initially from factory data; groups G5-G7 from BEST capacity test data. In addition, groups G1, G3 and G4 were also observed with features selected from the BEST capacity data. Therefore, changes in fabrication materials (groups G1/G3) have a continued effect on cell performance which was observed nearly three years after manufacture. However, clustering related to variations in the physical placement during formation (groups G2 and G4) was less emphasized for the BEST data, maybe because this factor became less important during early cell life. Groups G5-G7 were not understood, and no known material fabrication or operational variations are associated with these clusters.

3.3. Data from CEMC Operations

Battery maintenance data have been collected quarterly at CEMC since 1987. In March, 1989 and April, 1990, a set of 109-121 of the 324 cells were monitored for a capacity test, with data collected in the same manner as for the 1986 test at the BEST Facility. This subset was carefully selected to represent all cluster groups previously observed (Table 4) and to provide appropriate "control" sets with which each cluster group could be compared . Thus, statistical conclusions could be made considering the different behavior of previously identified cell clusters. Another capacity test was performed in September 1991, where all 323 operating cells were monitored.

3.3.1. Capacity Data Distributions

Cell capacity values appear to distribute with a single maximum in each distribution for the 450 A discharges conducted in March, 1989, April, 1990, and September, 1991 (Figure 4, 5, 6). The absence of any obviously unusual structure in the overall capacity distributions, however, does not preclude the existence of sub-groups of cells with uniform but distinct properties (see discussion below).

3.3.2. Statistical Tests

Table 5 summarizes the results of examining performance in the CEMC capacity tests of the various cell subsets identified in earlier capacity tests (Table 4), to determine if a statistically different performance continued to be exhibited by different sub-sets at later stages of cell lifetime. Cell clusters were compared with each other or with "control" sets. Control sets consisted of cells from previous cluster analysis studies which were not part of the cell cluster of interest, nor of any other observed clusters, but were part of the same fabrication batch.

The 1989 results in Table 5 examine the early mid-life behavior of the GNB cells, and indicate that capacity values for the previously identified cluster groups were significantly different from control sets except for two cases. The two exceptions are those clusters previously associated with inner/outer locations in formation corrals [2, 3]. Thus, it is concluded that the effects of material differences on performance continued to be observed. The early-life (BEST data) performance variations associated with environmental factors also continued to be observed. The effects of physical placement during formation became less important during mid-life operation.

The 1990 and 1991 results in Table 5 examine further the mid-life behavior of the battery. Statistical test results were the same as those from 1989, except for group G5 which no longer had a significant difference in capacities between the previously observed cluster and the control set. It should be pointed out that groups G1-G3 (material-dependent clusters) continue to show a significant difference on performance at end-life.

Table 3

Useful features (descriptors) from capacity test data.

Feature	Definition
NCAP	cell capacity during test cycle *N*
NFVLT	float voltage after test cycle *N*
NV*xxx*	cell voltage at *xxx* % nominal capacity
NSGB, NSGA	specific gravity before/after discharge *N*
DLCPNN	capacity change from one capacity test to the next
NDLV*x.y*	cell voltage change beyond nominal capacity, where *x*, *y* =8, 5, 0 for 108, 105, 100% capacity where *N*= F, from fabrication/test data B, from BEST capacity test cycle C, from CEMC capacity test cycle

Table 4

Cell clusters observed from factory and BEST data (1986 capacity test).

Group	Subsets	Cluster analysis features
G1	O/O grid/paste	DRYWT, AVSA, EQWF, SG4
(Circuit 1)	O/N grid/paste	
G2	outer cells	SG2, EQWF, MNCAP
(Circuit 2)	inner cells	AVCAP, AVSA, RNGSA
G3	O/N grid/paste	DRYWT, EQWF, MXCAP, MNCAP
(Circuit 3)	N/N grid/paste	AVCAP, MXSA, RNGSA
G4	outer cells	SG2, EQWF, MNCAP, AVCAP
(Circuit 4)	inner cells	AVSA, RNGSA
G5 (Circuit 1)	6-cell cluster (17, 21, 25, 36, 65, 74)	BCAP, DLCPBF, BFVLT, BV108, BDLV8.0
G6 (Circuit 2)	9-cell cluster (81, 82, 124, 128, 137, 139, 142, 143, 155)	BCAP, BV108, BDLV8.0
G7 (Circuit 2)	2-cell cluster (105, 109)	BCAP, DLCPBF, BFVLT, BV108, BDLV5.0

Table 5

Statistical differences in means of suspected cell clusters vs. control groups in CEMC capacity test in March, 1989 and April, 1990. t-Test applied at 95% confidence level.

Groups	Cell Subsets	Capacity % average ± standard deviation		Significant Difference	
		1989	1990	1989	1990
Group 1	O/O grid/paste	93.8±0.9	101.7±1.2	yes	yes
Circuit 1	O/N grid/paste	92.5±1.2	99.0±1.9		
Group 2	outer cells	93.6±1.3	101.7±0.7	no	no
Circuit 2	inner cells	93.8±2.3	100.9±2.3		
Group 3	O/N grid/paste	93.5±1.6	99.4±1.5	yes	yes
Circuit 3	N/N grid/paste	97.8±2.2	102.2±2.3		
Group 4	outer cells	98.8±2.7	104.1±3.1	no	no
Circuit 4	inner cells	96.8±2.6	103.0±2.5		
Group 5	observed cluster	90.7±1.5	97.0±1.1	yes	no
Circuit 1	control set	92.5±1.2	99.0±1.9		
Group 6	observed cluster	97.2±0.4	103.6±0.7	yes	yes
Circuit 2	control set	94.4±1.6	101.9±1.5		
Group 7	observed cluster	87.2±0.6	96.2±0.2	yes	yes
Circuit 2	control set	94.6±1.7	102.3±1.2		

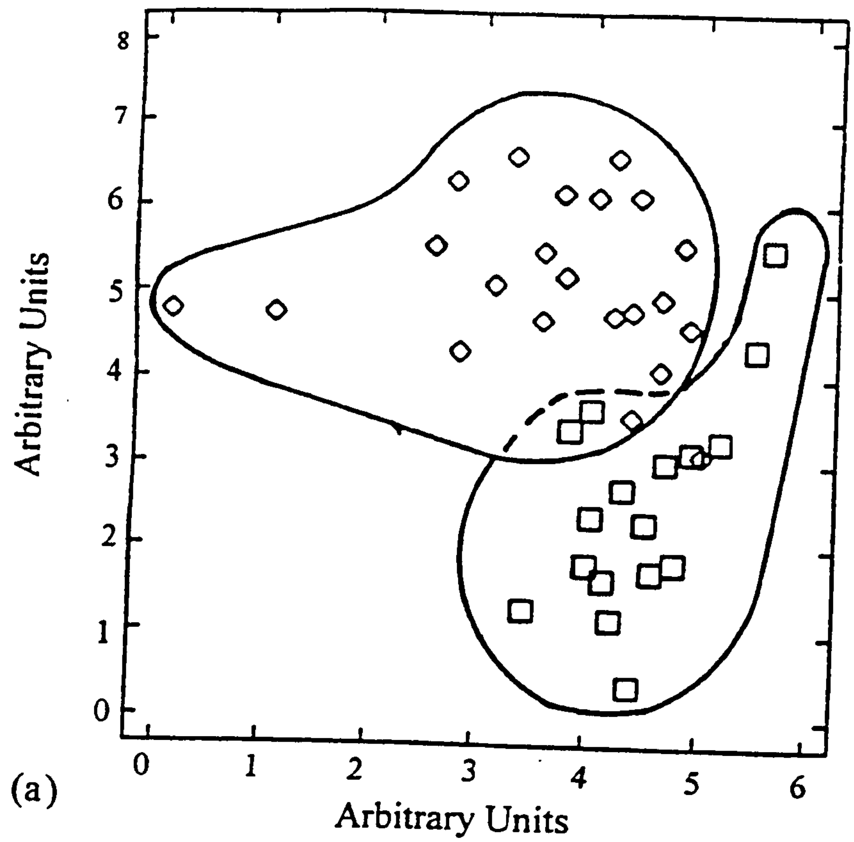
3.4. Performance Prediction from Initial Fabrication/Test Data

A previous study conducted by R. Petesch [4] attempted to determine if cell performance in mid- to late-life could be predicted from multivariate analysis of initial fabrication data. The data base used was the same as for cluster analysis studies [26, 27].

The cells were ranked according to the capacity values measured in April 1990 with the class boundaries defined as in section 2.2.3. Pattern recognition training for the high- and low-capacity cells (class 1 and class 2) resulted in overall classification accuracy up to 94.9% and the most consistently useful features were: AVSB, SHPSLFA, EQWC, ASHP, SG2, EQWF, RELFRMA, AVCAP (Table 1). For the three-class (high-, low- and intermediate capacity) training, the overall classification accuracy was as high as 76% with four features.

When nonlinear mapping was applied to the best two-class and three-class pattern recognition features, high- and low-capacity cells were well separated (Figure 9 (a)), but the clusters overlapped somewhat when all three classes were included (Figure 9 (b)).

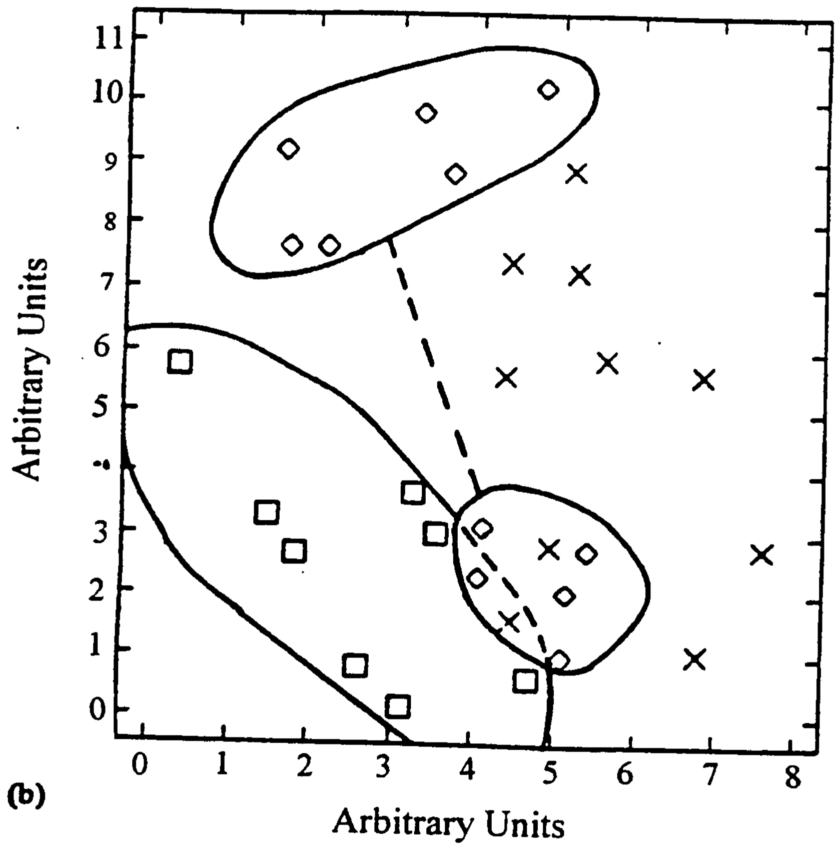
Re-classification was applied to some cells which were consistently displayed in the "wrong" clusters exhibited by NLM. Training procedures were then performed again after NLM re-classification (see section 2.2.6). For the two-class study, the results were as before. But for the three-class study, the overall training classification accuracy was increased from 76% to 86%. The prediction ability of the useful feature sets identified by this training procedure was evaluated by classifying cells from class 3 which had not been included in the training set. The prediction classification accuracy was only 48%, which



(a)

Figure 9. Non-linear mapping (NLM) of GNB cell fabrication-test features, used for pattern recognition classification of April, 1990, capacity data. □ = High-capacity cells (class 1); ◆ = low-capacity cells (class 2); × = intermediate-capacity cells (class 3).

(a) Two-class (high/low/capacity classification), useful features: SG2, EQWC, ASHP, SHPSLFA, AVSB, AVCAP.



(b)

Figure 9. Non-linear mapping (NLM) of GNB cell fabrication-test features, used for pattern recognition classification of April, 1990, capacity data. □ = High-capacity cells (class 1); ◆ = low-capacity cells (class 2); × = intermediate-capacity cells (class 3).

(b) Three-class (high/low/intermediate-capacity classification), successful features: SG2, EQWF, SG4, ASHPA, SHPSLFA [2].

was unsatisfactory. However, the training and NLM results at least confirmed that information related to mid-life performance behavior was contained in cell fabrication data.

3.5. Performance Prediction from Maintenance Data

Another previous study by Chen [26] attempted to determine if individual cell performance could be predicted from periodic maintenance data. The data base consisted of all maintenance data (float voltages, specific gravities, water added, electrolyte levels) collected quarterly between August, 1987 and February, 1990. Maintenance data collected prior to the 1989 capacity test were used for training set features, whereas similar data collected in the year prior to the 1990 capacity test were used for prediction set features. The class boundaries were defined as in section 2.2.3.

This prior study demonstrated the importance of data organization procedures for successful pattern recognition from maintenance data. The three data organization methods investigated involved indexing maintenance measurement by specific month, by elapsed time, and by battery activity. This last index was established from water-added data, and was found to be the most useful. The feature definitions are summarized in Table 6. Classification accuracies for two-class training and three-class training were 100% and 86%, respectively. The two-class prediction accuracy was 94%; the three-class prediction accuracy was 57%. The results were encouraging, although not highly accurate for prediction. Again, as for the pattern recognition study with fabrication data, it was clear that information related to performance prediction was contained in the maintenance

Table 6

Maintenance Features Used for Time or Battery Activity Index Investigations.

Each item refers to measurements made quarterly for a specific cell[a].

Feature	Definition
CELVOLT(t-1),...,	normalized cell float voltage values for (t-1)...to (t-4)
CELVOLT(t-4)	where (t-1) is the maintenance event immediately
	preceding the capacity test, and (t-4) is the 4th
	(earliest) event preceding the capacity test.
SPGR(t-1),... SPGR(t-4)	normalized specific gravity values indexed as above
LEVEL (t-1),...LEVEL(t-4)	normalized electrolyte level values indexed as above
WATER(t-1),...WATER(t-4)	normalized water addition values indexed as above
NCLVX/Y	[CELVOLT(t-X)-CELVOLT(t-Y)][b]
NSGX/Y	[SPGR(t-X)-SPGR(t-Y)]
NLVLX/Y	[LEVEL(t-X)-LEVEL(t-Y)]
NWATX/Y	[WATER(t-X)-WATER(t-Y)]
AVGVLT	average value of cell voltages over all maintenance events
AVGSPGR	average value of specific gravities over all
	maintenance events
AVGLVL	average value of electrolyte levels over all
	maintenance events
AVGWAT	average value of water-added over all
	maintenance events
SG*AV	[(AVSPGR)*(AVGVLT)]
AV/SG	[(AVGVLT)/(AVGSPGR)]
PVLT	product of cell voltages from all maintenance events
RELWAT	ratio of cumulative water-added (1...4) to average
	over all cells
SLPCLV	slope for cell voltages ((t-1)...(t-4))
SLPSG	slope for specific gravities ((t-1)...(t-4))
SLPLVL	slope for electrolyte levels ((t-1)...(t-4))
SLPWAT	slope for water-added ((t-1)...(t-4))

[a] For battery activity index, substitute T for t, where T-1 corresponds to the maintenance event following the highest battery activity as measured by water consumption, and T-4 corresponds to that with the lowest battery activity.

[b] X,Y=1,...,4

data, but prediction accuracy was still not satisfactory for realistic applications to cells of unknown class.

3.6. Performance Prediction from Combination Data -- Fabrication and Maintenance Data

Because individual lead/acid cell performance prediction results were not satisfactory from either fabrication data or maintenance data, further studies are reported here which combine cell fabrication data and maintenance data to examine high-, low-, and intermediate-capacity cell performance. In this study, fabrication data contain 13 features: ASHPA, AVCAP, AVSA, AVSB, DRYWT, SG2, SG4 and SHPSLFA (defined in Table 1). And maintenance data include 9 features: AVGVLT, AVGLVL, NCLV3/4, NCLV1/3, NSG1/4, PVLT, NLVL1/2, LEVEL(T-2) and NWAT2/4 (defined in Table 6).

3.6.1. Performance Classification from Fabrication Data and from Maintenance Data Collected in 1989, 1990.

Combination features in which maintenance data were collected prior to the 1989 capacity test were used for training set. Prediction sets were obtained from combination features where the maintenance data were collected prior to the 1990 capacity test. There were 42 cells included in both the training and prediction sets, equally divided among class 1, 2, and 3 based on cell performance in 1989, 1990. Only those 9 maintenance features and 13 fabrication features (see above) found useful earlier [2, 4, 26] were included in the training and prediction sets.

3.6.1.1. Training and Prediction

The best training results are shown in Table 7. Overall training classification accuracy was as high as 88.1%, and the highest individual accuracies obtained from meaningful classifiers were 100%, 100%, and 71.4% for class 1, class 2, and class 3, respectively. By comparison, the study only on fabrication data provided best overall training classification accuracy of 86% (after re-classification), and specific class accuracies were 85%, 92%, 81%, respectively. The study on maintenance data (only water-added index) provided classification accuracy of 100%, and specific class accuracies of 100%, 100%, 100% respectively (after re-classification). In both of these cases the highest accuracy was achieved only after re-classifying anomalous cells. Therefore, the initial training results with combined data were very encouraging. The results (Table 7) indicated that features NLVL1/2 and DRYWT seemed to be necessary but not sufficient for separating all three classes.

A three-class prediction set based on the April, 1990 capacity test was examined using the best four feature sets from the training results, and Table 8 lists the prediction results. Overall prediction accuracy as high as 59.5% was observed. By comparison, the best prediction overall classification accuracy with fabrication data was ~ 48%; and with maintenance data (only water-added index), the best overall classification accuracy was 60%. In both of these cases the highest accuracy was achieved only after re-classifying anomalous cells. But the combination data study provided higher or similar overall classification accuracy, even with anomalous cells included. In addition, Table 8 provides some meaningful insight by also including false-positive data. These encouraging results prompted further studies, using NLM re-classification of anomalous cells and, for the first time, investigation of class-weighted training procedures.

Table 7

Combination data training best results for 3-class pattern set.

Maintenance data collected prior to March, 1989, capacity test[a].

% Classification Accuracy Overall/ Class1/ Class2/ Class3	Feature Used (weights)
88.1 / 92.9 / 100 / 71.4	NCLV1/3, AVGVLT, NLVL1/2, SHPLFA, DRYWT(2)
85.7 / 100 / 85.7 / 71.4	NCLV3/4(4), NLVL1/2, ASHP, EQWF(2), SG4, EQWC, AVSA, DRYWT, PVLT
85.7 / 100 / 85.7 / 71.4	NLVL1/2, DRYWT, AVSA(2), SG2(2), NWAT2/4(2), AVGLVL
83.3 / 100 / 85.7 / 64.3	NCLV1/3, NSG1/4, NLVL1/2, SHPLFA, AVCAP, DRYWT

[a] Total patterns: 42, Class 1 = high-capacity cells (14), Class 2 = low-capacity cells(14), and Class 3 = intermediate-capacity cells (14).

Table 8

Combination data prediction best results for 3-class pattern set.

Maintenance data collected prior to April, 1990, capacity test[a].

Auto scaling[b]	FP[c] Cls1	FP[c] Cls2	% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
I	4	5	47.6 / 50.0 / 23.1 / 64.7	NLVL1/2, SG2, NCLV1/3, NSG1/4, SHPLFA, AVCAP, DRYWT
J	5	3	45.2 / 58.3 / 23.1 / 52.9	PVLT, NCLV3/4, SG4, EQWC, ASHP, NLVL1/2, EQWF(2), AVSA, MXCAP, DRYWT
I	13	3	54.8 / 58.3 / 61.5 / 47.1	NWAT2/4(2), AVGLVL, SG2(2), NLVL1/2, AVSA(2), DRYWT
I or J	10	4	59.5 / 75.0 / 69.2 / 41.2	NWAT2/4, AVGLVL, AVSB, RELFRMA, AVSB(2)

[a] Total patterns: 42, Class 1 = high-capacity cells (12), Class 2 = low-capacity cells (13), Class 3 = intermediate-capacity cells (17).

[b] Two options: Joint or individual autoscaling. Selecting "J" (JOINT), training and prediction sets scaled together; selecting "I" (INDIVIDUAL), training set autoscaled as a block; then, uses average and standard deviation from training set to autoscale each prediction pattern.

[c] FP = false positive

By examining the non-linear mapping plots of the various feature sets useful for training, it was observed that three fairly well-defined separate clusters of cells did exist, but a few cells were found to fall consistently in clusters of a different class (see Figure 10). These were reclassified as follows:

Number of Cell	New Class	Old Class
14	1	3
41, 78, 196	2	3

The training procedure was repeated, including re-classified cells, and the results are listed in Table 9. Compared to Table 7, the results were changed little. However, higher accuracy prediction results were obtained (compare Table 10 to Table 8).

3.6.1.2. Class-Weighted Training and Prediction

The class-weighted training procedure used in this work was described in section 2.2.8. Results are given in Table 11. Class 1 or class 2 cells could be identified with greater than 85.7% accuracy, each with three different sets of features. Note that one feature set allowed class 1 cells to be identified with 100% accuracy and with only 1 false positive. And class 2 cells could be identified with only 2 false positives with 100% accuracy for one feature set. For each of these cases overall accuracy was modest or poor (88.1%, 66.7%). However, it is clear that the identification of either high- or low-performance cells separate from the rest can be done with higher accuracy using specific feature sets.

Class-specific prediction classification was conducted using the same feature sets selected by the preceding training study, and the best results are listed in Table 12. Non-linear mapping plots were also examined for the best class-weighted training feature to determine if any anomalous cells should be re-classified. The following cell classes were changed:

Number of Cell	New Class	Old Class	Class-Weighted
247, 267, 307	1	3	1
24, 41	2	3	2
28	1	2	2

The class-weighted training procedure was repeated after re-classifying cells and Table 13 lists the best results. As expected, higher classification accuracies were obtained, up to 100% for both class 1 or class 2 with no false positives; overall classification accuracies were 92.9%, 85.7%, respectively.

Class-specific prediction was again performed based on the revised sets of useful class-weighted training features. The accuracy of prediction results (Table 14) was improved little compared to before re-training (Table 12).

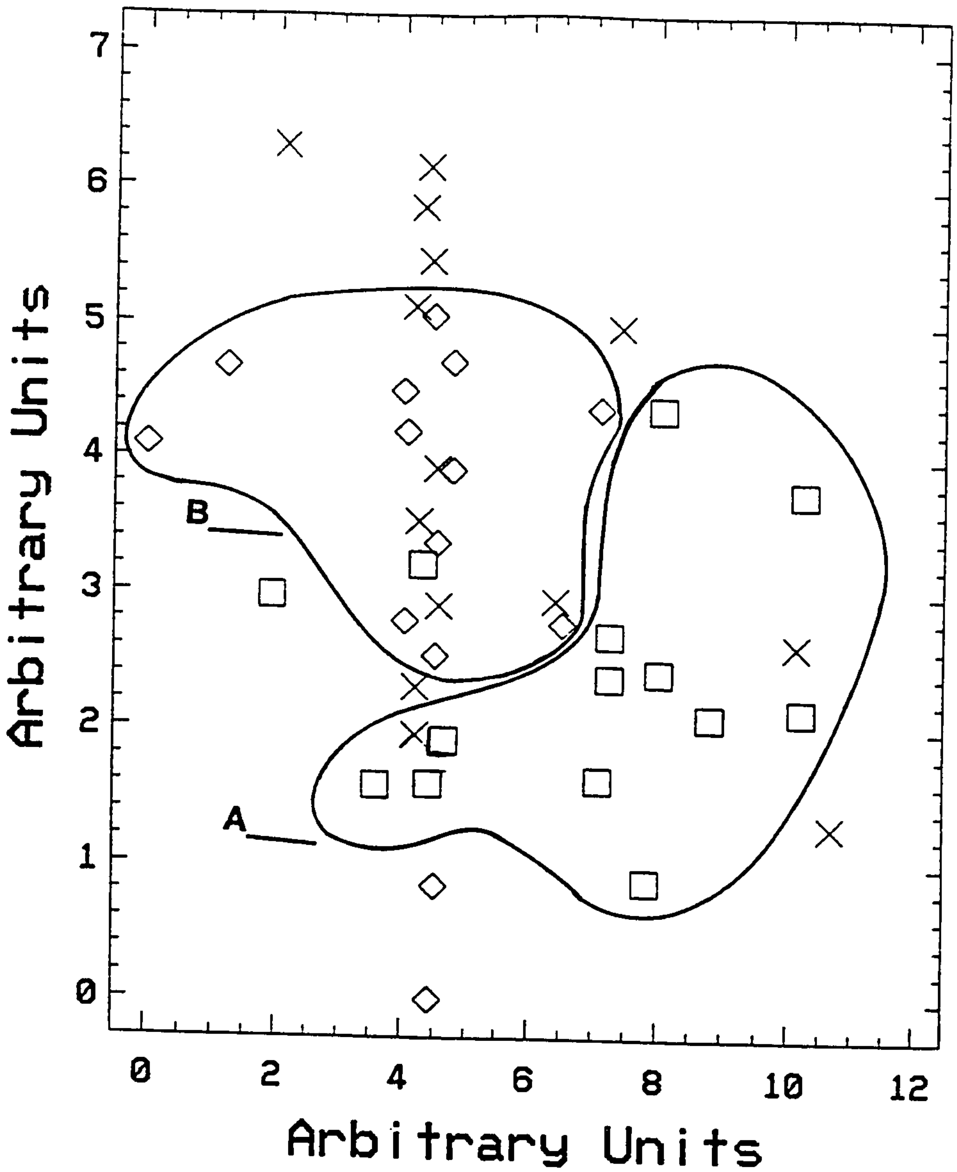


Figure 10. Non-linear mapping (NLM) of GNB cell fabrication and maintenance features. Maintenance data collected at CEMC prior to March, 1989 capacity test. The iteration number is 1000 and useful features: NCLV1/3, AVSA, DRYWT(2). □ = High-capacity cells (class 1) ◆ = low-capacity cells (class 2) × = intermediate-capacity cells (class 3).

Table 9

Combination data training best results for 3-class pattern set after NLM (1000 iterative cycles) re-classification.

Maintenance data collected prior to March, 1989, capacity test[a].

% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
88.1 / 100 / 88.1 / 70.0	NCLV1/3, AVGVLT, NLVL1/2, AVSA, SHPLFA, NSG1/4(2), AVGLVL, MXSA
85.7 / 93.3 / 94.1 / 60.0	NCLV3/4(2), DRYWT, MXSA(2), SHPLFA
85.7 / 93.3 / 94.1 / 60.0	NLVL1/2(2), DRYWT(2), AVSA, SG2, ASHP, MXCAP
83.3 / 86.7 / 100 / 50.0	NCLV1/3, NSG1/4, NLVL1/2(2), EQWC, ASHP, SHPLFA(2), DRYWT
83.3 / 86.7 / 94.1 / 60.0	NCLV1/3, SG2, ASHP, NLVL1/2, AVSA, DRYWT(2)
83.3 / 93.3 / 94.1 60.0	PVLT(2), NLVL1/2, RELFRMA

[a] Total patterns: 42, Class 1 = high-capacity cells (15), Class 2 = low-capacity cells(17), and Class 3 = intermediate-capacity cells (10).

Table 10

Combination data prediction best results for 3-class pattern set after NLM re-classification.

Maintenance data collected prior to April, 1990, capacity test[a].

Auto scaling[b]	FP[c] Cls1	Cls2	% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
J	2	11	50.0 / 50.0 / 61.5 / 41.2	EQWF(4), EQWC, SHPLFA, AVGVLT, NCLV1/3, DRYWT
I	4	6	57.1 / 75.0 / 61.5 / 41.2	EQWF(4), EQWC, SHPLFA, AVGVLT, NCLV1/3, DRYWT
I or J	5	7	61.9 / 83.3 / 69.2 / 41.2	NCLV3/4(2), MXSA(2), SHPLFA, DRYWT

[a] Total patterns: 42, Class 1 = high-capacity cells (12), Class 2 = low-capacity cells (13), Class 3 = intermediate-capacity cells (17).

[b] Two options: Joint or individual autoscaling. Selecting "J" (JOINT), training and prediction sets scaled together; selecting "I" (INDIVIDUAL), training set autoscaled as a block; then, uses average and standard deviation from training set to autoscale each prediction pattern.

[c] FP = false positive

Table 11

Combination data CWD training best results for 3-class pattern set.

Maintenance data collected prior to March, 1989, capacity test[a].

CWD	FP	% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
1	1	66.7 / 100 / 50.0 / 50.0	PVLT(2), AVSB, MXSA, AVSA, MXCAP, DRYWT(2)
	1	81.0 / 92.9 / 78.6 / 71.4	NLVL1/2, AVSA, DRYWT, MXCAP
	1	61.9 / 85.7 / 50.0 / 50.0	NSG1/4, NWAT2/4, MXCAP
2	2	88.1 / 92.9 / 100 / 71.4	AVGVLT, NCLV1/3, SHPLFA, NLVL1/2, DRYWT(2)
	2	88.1 / 100 / 92.9 / 71.4	EQWF, LEVEL(T-2), NSG1/4, DRYWT, NCLV1/3, SHPLFA
	2	78.6 / 78.6 / 92.9 / 64.3	AVGLVL, RELFRMA, NLVL1/2, SHPLFA(2), AVSB, AVSA, DRYWT, MXCAP(2)

[a] Total patterns: 42, Class 1 = high-capacity cells (14), Class 2 = low-capacity cells(14), and Class 3 = intermediate-capacity cells (14).

To assess the value of class-specific prediction results, one needs to consider the differing goals for selecting class 1 and class 2 cells. Successful identification of class 1 (high-performance) cells should include a minimum number of false positives because the intent is use these cells in demanding applications. Thus, high accuracy is important, but low number of false positives is a higher priority. Considering all prediction studies, the best results for class 1 recognition were obtained with class-weighted training (Table 10). Class 1 prediction accuracy was 50.0% with 2 false positive; i.e., 75% of the high performance cells identified were correctly selected.

For class 2 (poor performance) cells, the objective is to eliminate them from crucial applications. Therefore, high accuracy recognition is the higher priority, false positives might be eliminated unnecessarily, but this may be tolerable. The best results for class 2 are reported in Table 14. Class 2 classification accuracy was 84.6% with 3 false positives.

Table 12

Combination data prediction best results followed CWD training.

Maintenance data collected prior to April, 1990, capacity test[a].

CWD	Auto scaling[b]	FP[c]	% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
1	J	1	42.9 / 16.7 / 46.2 / 58.8	SG2, EQWF, EQWC, NCLV3/4, SHPLFA
	J	4	57.1 / 75.0 / 84.6 / 23.5	PVLT(2), AVSB, MXSA, AVSA, DRYWT(2), MXCAP
	I	2	47.6 / 33.3 / 46.2 / 58.8	SG2, EQWF, EQWC, NCLV3/4, SHPLFA
	J	6	61.9 / 91.7 / 38.5 / 58.8	NLVL1/2, AVSA, MXCAP, DRYWT
2	I	2	73.8 / 83.3 / 76.9 / 64.7	AVGLVL, RELFRMA,AVSB, SHPLAF(2), NLVL1/2, AVSA, DRYWT, MXCAP(2)
	I	5	54.8 / 66.7 / 53.8 / 47.1	NCLV3/4, EQWF, AVGVLT, NCLV1/3, NSG1/4, SHPLFA, AVCAP

[a] Total patterns: 42, Class 1 = high-capacity cells (12), Class 2 = low-capacity cells (13), Class 3 = intermediate-capacity cells (17).

[b] Two options: Joint or individual autoscaling. Selecting "J" (JOINT), training and prediction sets scaled together; selecting "I" (INDIVIDUAL), training set autoscaled as a block; then, uses average and standard deviation from training set to autoscale each prediction pattern.

[c] FP = false positive

Table 13

Combination data CWD training best results for 3-class pattern set after NLM re-classification.

Maintenance data collected prior to March, 1989, capacity test[a].

CWD	FP	% Classification Accuracy Overall/ Class1/ Class2/ Class3	Feature Used (weights)
1	0	90.5 / 100 / 85.7 / 81.8	AVGVLT, NSG1/4, AVCAP, NCLV1/3, SHPLFA
	0	90.5 / 100 / 85.7 / 81.8	NLVL1/2, AVGVLT, SHPLFA, DRYWT, NCLV1/3, AVCAP
	0	90.5 / 100 / 92.9 / 72.7	NLVL1/2, NCLV1/3, DRYWT, SHPLFA, RELFRMA
	0	92.9 / 100 / 85.7 / 90.9	NCLV3/4(2), EQWF, NLVL1/3, AVSA(2), ASHP, MXCAP(2)
	0	92.9 / 100 / 92.9 / 81.8	NCLV1/3, NLVL1/2, PVLT, SHPLFA, DRYWT
2	0	83.3 / 86.7 / 100 / 58.3	NCLV1/3, SHPLFA(2), EQWC(2), SG2, DRYWT
	2	85.7 / 86.7 / 100 / 66.7	SHPLFA, LEVEL(T-2), AVGVLT, AVSA, NCLV1/3, AVSB, RELFRMA, DRYWT
	2	78.6 / 80.0 / 100 / 50.0	NCLV1/3, EQWC, SG2, ASHP, DRYWT

[a] Total patterns: 42,

CWD 1: Class 1 = high-capacity cells (17), Class 2 = low-capacity cells(14), and Class 3 = intermediate-capacity cells (11).

CWD 2: Class 1 = high-capacity cells (15), Class 2 = low-capacity cells(15), and Class 3 = intermediate-capacity cells (12).

Table 14

Combination data prediction best results for CWD training after NLM re-classification. Maintenance data collected prior to April, 1990, capacity test[a].

CWD	Auto scaling[b]	FP[c]	% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
1	J	3	42.9 / 41.7 / 15.4 / 64.7	NLVL1/2, AVGVLT, AVCAP, NCLV1/3, SHPLFA, DRYWT
	J	3	40.5 / 33.3 / 15.4 / 64.7	NCLV3/4(2), EQWF, ASHP, NLVL1/2, AVSA(2), MXCAP(2)
	J	6	54.8 / 91.7 / 30.8 / 47.1	NCLV3/4(2), ASHP, AVSA, NLVL1/2, DRYWT, MXCAP(4)
2	I or J	3	71.4 / 83.3 / 84.6 / 52.9	AVGLVL, RELFRMA, AVSA, SHPLFA, AVSB, MXCAP
	I or J	4	71.4 / 83.3 / 84.6 / 52.9	SG2, ASHP, AVSA, DRYWT
	I	6	59.5 / 66.7 / 69.2 / 47.1	LEVEL(T-2), AVGLVL, ELFRMA, AVSB,AVSA, NCLV1/3, SHPLFA, DRYWT

[a] Total patterns: 42, Class 1 = high-capacity cells (12), Class 2 = low-capacity cells (13), Class 3 = intermediate-capacity cells (17).

[b] Two options: Joint or individual autoscaling. Selecting "J" (JOINT), training and prediction sets scaled together; selecting "I" (INDIVIDUAL), training set autoscaled as a block; then, uses average and standard deviation from training set to autoscale each prediction pattern.

[c] FP = false positive

3.6.2. Performance Prediction from Fabrication Data and from Maintenance Data Collected in 1990, 1991.

In this study, the combination features used for training included maintenance data collected prior to the 1990 capacity test. For prediction set, combination features included maintenance data collected prior to the 1991 capacity test. As with the preceding studies, the same 9 useful maintenance features and 13 fabrication features were used to define the training and prediction feature sets. There were 42 and 50 cells in training and prediction sets respectively. The larger number of cells included in the prediction set was due to the fact that the capacity test in September 1991 was performed on all 323 operating cells.

3.6.2.1. Training and Prediction

Training was conducted and the best results are shown in Table 15. Overall classification accuracy generally fell between 71.4% to 76.2%, and the highest individual accuracies obtained from meaningful classifiers were 91.7%, 92.3%, and 70.6% for class 1, class 2, and class 3, respectively. A three-class prediction set based on class assignments from the September, 1991, capacity test was examined using the best sets of features from the training results. Table 16 lists the best prediction results.

By examining the non-linear mapping plots of the various useful training feature sets, it was observed that three fairly well-defined separate clusters of cells did exist (see Figure 11), but a few anomalous cells were found and were reclassified as follows:

Number of Cell	New Class	Old Class
24, 41, 78	2	3
234, 235, 242, 247, 263	1	3

The training procedure was repeated with re-classified cells, and the results are listed in Table 17. As expected, the accuracy was improved. The subsequent prediction results (Table 18) were comparable to those reported without re-classification (Table 16).

3.6.2.2. Class-Weighted Training and Prediction

As described earlier (section 2.2.8), class-weighted training was conducted on the 1990 training set. The results (Table 19) showed that overall training classification as high as 81.0% could be achieved with 100% class 1 recognition and 2 false positives. 78.6% overall training accuracy was achieved with 92.3% class 2 recognition and 1 false positive.

As before, the prediction procedure was conducted based on the class-weighted training results, and the best prediction results are listed in Table 20. These results were disappointing. Non-linear mapping plots were also examined for the class-weighted training set. The following cell classes were changed:

Number of Cell	New Class	Old Class	Class-Weighted
93, 133, 242	1	3	1
41, 90	2	3	2
14	2	1	2

The training procedure was repeated after re-classifying cells and Table 21 lists the best results. The results were similar to those in Table 19. The prediction procedure again was performed based on revised class weighted training results. The results (Table 22) were improved slightly compared to those in Table 20.

Table 15

Combination data training best results for 3-class pattern set.

Maintenance data collected prior to April, 1990, capacity test[a].

% Classification Accuracy Overall/ Class1/ Class2/ Class3	Feature Used (weights)
76.2 / 91.7 / 84.6 / 58.8	NSG1/4, NWAT2/4, SG2, EQWC(4), ASHP(2), RELFRMA(4)
76.2 / 83.8 / 84.6 / 64.7	NCLV3/1(2), AVGVLT, NCVL3/4(4)
76.2 / 75.0 / 92.3 / 64.7	AVGVLT(4), NCLV3/1(2), ASHP(2), SHPLFA
76.2 / 83.8 / 76.9 / 64.7	LEVLE(T-2), SG2, EQWF(4), AVGLVL, NVLV2/1, SHPLFA(2)
73.8 / 83.8 / 76.9 / 64.7	NCLV3/4, NSG1/4, ASHP(2), AVSB, RELFRAM, NLVL2/1, SHPLFA, MXSA(2)
71.4 / 83.8 / 76.9 / 58.8	ASHP, PVLT(2)

[a] Total patterns: 42, Class 1 = high-capacity cells (12), Class 2 = low-capacity cells(13), and Class 3 = intermediate-capacity cells (17).

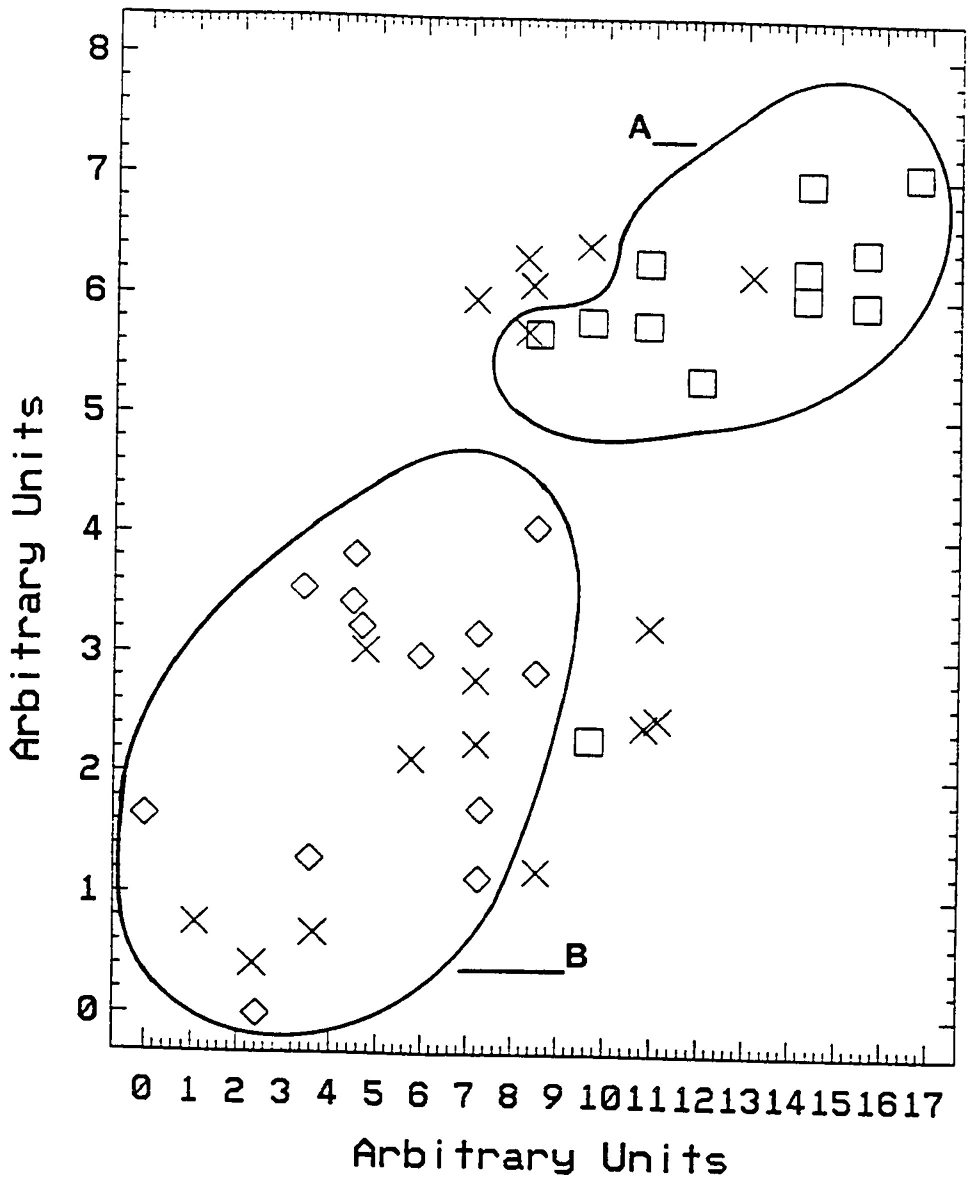


Figure 11. Non-linear mapping (NLM) of GNB cell fabrication and maintenance features. Maintenance data collected at CEMC prior to September. 1990 capacity test. The iteration number is 1000 and useful features: AVGVLT(4). NCLV3/1(2), ASHP(2), SHPLAF. □ = High-capacity cells (class 1) ◆ = low-capacity cells (class 2) × = intermediate-capacity cells (class 3).

Table 16

Combination data prediction best results for 3-class pattern set.

Maintenance data collected prior to September, 1991, capacity test[a].

Auto scaling[b]	FP[c] Cls1	FP[c] Cls2	% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
J	6	5	48.0 / 50.0 / 37.5 / 55.6	LEVEL(T-2), SG2, NLVL2/1, EQWF(4), AVGLVL, SHPLFA(2)
I	7	6	56.0 / 56.3 / 62.5 / 50.0	AVGLVL, NLVL2/1, AVSB, MXCAP, MXSA, NCLV3/4
I	9	7	54.0 / 50.0 / 56.3 / 55.6	NCLV3/4, NSG1/4, ASHP(2), RELFRMA, NLVL2/1, MXSA(2), SHPLFA, AVSB,

[a] Total patterns: 50, Class 1 = high-capacity cells (16), Class 2 = low-capacity cells (16), Class 3 = intermediate-capacity cells (18).

[b] Two options: Joint or individual autoscaling. Selecting "J" (JOINT), training and prediction sets scaled together; selecting "I" (INDIVIDUAL), training set autoscaled as a block; then, uses average and standard deviation from training set to autoscale each prediction pattern.

[c] FP = false positive

Table 17

Combination data training best results for 3-class pattern set after NLM re-classification. Maintenance data collected prior to April, 1990, capacity test[a].

% Classification Accuracy Overall/ Class1/ Class2/ Class3	Feature Used (weights)
90.5 / 94.1 / 93.8 / 77.8	NSG1/4, LEVEL(T-2), EQWF(4), EQWC, NLVL2/1(2), SHPLFA(2)
88.1 / 94.1 / 100 / 55.6	LEVEL(T-2), SG2, EQWF(4), NLVL2/1, AVGLVL, SHPLFA(2)
90.5 / 88.2 / 93.8 / 88.9	NCLV3/1, EQWF(2), NWAT2/4, NLVL2/1, SHPLFA(4)
88.1 / 94.1 / 93.8 / 66.7	ASHP, RELFRMA(2), AVSB, NLVL2/1, MXSA
88.1 / 94.1 / 93.8 / 66.7	ASHP, RELFRMA(2), MXSA, NLVL2/1, NCLV3/4

[a] Total patterns: 42, Class 1 = high-capacity cells (17), Class 2 = low-capacity cells(16), and Class 3 = intermediate-capacity cells (9).

Table 18

Combination data prediction best results for 3-class pattern set after NLM re-classification.

Maintenance data collected prior to September, 1991, capacity test[a].

Auto scaling[b]	FP[c] Cls1	FP[c] Cls2	% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
J	9	8	52.0 / 75.0 / 56.3 / 27.8	NLVL2/1, SHPLFA, AVSA(2), MXCAP
J	10	8	54.0 / 68.8 / 62.5 / 33.3	NSG1/4, AVSA(2), DRYWT, MXCAP(2)
J	8	14	40.0 / 43.8 / 62.5 / 16.7	LEVEL(T-2), NLVL2/1(2), SG2, EQWF, PVLT, NCLV3/4(2)

[a] Total patterns: 50, Class 1 = high-capacity cells (16), Class 2 = low-capacity cells (16), Class 3 = intermediate-capacity cells (18).

[b] Two options: Joint or individual autoscaling. Selecting "J" (JOINT), training and prediction sets scaled together; selecting "I" (INDIVIDUAL), training set autoscaled as a block; then, uses average and standard deviation from training set to autoscale each prediction pattern.

[c] FP = false positive

Table 19

Combination data CWD training best results for 3-class pattern set.

Maintenance data collected prior to April, 1990, capacity test[a].

CWD	FP	% Classification Accuracy Overall/ Class1/ Class2/ Class3	Feature Used (weights)
1	0	64.3 / 58.3 / 69.2 / 64.7	DRYWT, NCLV3/1, RELFRMA, NLVL2/1, SHPLFA
	2	81.0 / 100 / 71.4 / 71.4	AVGLVL, NLVL1/2, DRYWT(2), NCLV1/3, SHPLFA, MXSA
2	1	78.6 / 66.7 / 92.3 / 76.5	AVGVLT, ASHP, PVLT, NCLV3/4
	3	71.4 / 66.7 / 92.3 / 58.8	NSG1/4, ASHP(2), NLVL3/4, RELFRMA(8)

[a] Total patterns: 42, Class 1 = high-capacity cells (12), Class 2 = low-capacity cells(13), and Class 3 = intermediate-capacity cells (17).

Table 20

Combination data prediction best results for CWD training.

Maintenance data collected prior to September, 1991, capacity test[a].

CWD[b]	Auto scaling[c]	FP[d]	% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
1	J	7	38.0 / 50.0 / 43.8 / 22.2	NCLV3/4, NSG1/4, MXSA, LEVEL(T-2), EQWF, SG2, AVGLVL, NLVL2/1, SHPLFA, MXCAP
	J	4	36.0 / 25.0 / 31.3 / 50.0	AVGLVL(4), NLVL2/1, PVLT, SHPLFA(2), DRYWT, NCLV3/4
2	I	6	58.0/ 50.0 / 62.5 / 61.1	NLVL2/1, SHPLFA, AVSB, MXCAP, MXSA, PVLT, NCLV3/4
	J	7	62.0 / 56.3 / 62.5 / 66.7	NLVL2/1, SHPLFA, AVSB, MXCAP, MXSA, NCLV3/4, PVLT

[a] Total patterns: 50, Class 1 = high-capacity cells (16), Class 2 = low-capacity cells (16), Class 3 = intermediate-capacity cells (18).

[b] CWD = class-weighted

[c] Two options: Joint or individual autoscaling. Selecting "J" (JOINT), training and prediction sets scaled together; selecting "I" (INDIVIDUAL), training set autoscaled as a block; then, uses average and standard deviation from training set to autoscale each prediction pattern.

[d] FP = false positive

Table 21

Combination data CWD training best results for 3-class pattern set after NLM re-classification. Maintenance data collected prior to April, 1990, capacity test[a].

CWD[b]	FP[c]	% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
1	1	66.7 / 93.3 / 69.2 / 35.7	AVGVLT(2), ASHP, MXSA, RELFRAM, DRYWT, AVGLVL, SHPLFA(8)
	1	64.3 / 86.7/ 69.2 / 35.7	MXSA, SHPLFA, PVLT, LEVEL(T-2), MXCAP
2	3	78.6 / 63.6 / 100 / 66.7	NSG1/4, SHPLFA(4), AVSB, DRYWT, NCLV3/4
	1	73.8 / 72.7 / 93.8 / 53.3	ASHP, AVSA(4), NWAT2/4, MXSA, NLVL2/1(2), DRYWT, MXCAP(2)

[a] Total patterns: 42,
CWD 1: Class 1 = high-capacity cells (157), Class 2 = low-capacity cells(13), and Class 3 = intermediate-capacity cells (14).
CWD 2: Class 1 = high-capacity cells (11), Class 2 = low-capacity cells(16), and Class 3 = intermediate-capacity cells (15).

[b] CWD = class-weighted

[c] FP = false positive

Table 22

Combination data prediction best results for CWD training after NLM re-classification. Maintenance data collected prior to September, 1991, capacity test[a].

CWD[b]	Auto scaling[c]	FP[d]	% Classification Accuracy Overall/Class1/Class2/Class3	Feature Used (weights)
1	I	8	42.0 / 56.3 / 37.5 / 33.3	NCVL3/4(2), NSG1/4, EQWF, NWATER2/4, AVGLVL, SG2, SHPLFA, MXCAP(2), MXSA, NLVL2/1
	J	6	44.0 / 50.0 / 56.3 / 27.8	MXSA, NSG1/4, SG2, SHPLFA, NWAT2/4, AVGLVL, NLVL2/1, EQWF, MXCAP(2), NCVL3/4(2)
	J	9	40.0 / 62.5 / 31.3 / 27.8	NSG1/4(2), ASHP, SHPLFA(2), MXCAP
2	I	8	54.0 / 43.8 / 62.5 / 55.6	ASHP, AVSA(4), DRYWT, SHPLFA(2), MXCAP(2), MXSA, NWAT2/4
	J	9	56.0 / 43.8 / 68.8 / 55.6	ASHP, AVSA(4), DRYWT, SHPLFA(2), MXCAP(2), MXSA, NWAT2/4

[a] Total patterns: 50, Class 1 = high-capacity cells (16), Class 2 = low-capacity cells (16), Class 3 = intermediate-capacity cells (18).

[b] CWD = class-weighted

[c] Two options: Joint or individual autoscaling. Selecting "J" (JOINT), training and prediction sets scaled together; selecting "I" (INDIVIDUAL), training set autoscaled as a block; then, uses average and standard deviation from training set to autoscale each prediction pattern.

[d] FP = false positive

3.7. Evaluation of Cell Re - Classification / Re - Training Procedures

One technique used successfully in this work to improve prediction classification accuracy is to identify "anomalous" cells and re-classify them, for training, as belonging to the cell sub-set with which they apparently cluster in feature space. This method allows the training procedure to proceed without undue influence by a few cells whose measured features are inconsistent with their performance class. The resultant useful feature sets generally provide more accurate prediction classification.

The cell re-classification/training procedure is critically dependent on the validity of NLM displays, as these are examined visually to identify anomalous cells. The NLM procedure provides an admittedly distorted two-dimensional display of higher-dimensional feature space. The mapping error can be reduced with further iterations [18,19], but the procedure is normally terminated when minimal changes occur with successive iterations.

For most of the work, 1000 NLM iterations appeared to be adequate. However, a study conducted to evaluate the effects of numbers of iterations on the visual displays, and specifically on the identification of anomalous cells. Figure 12 and 13 demonstrate changes in the mapping for one 1989 feature set with 1000 and 8000 iterations, respectively. The impact of this variable on identifying anomalous cells is described below.

Selected for evaluation were the combination data which included the 1989 maintenance measurements. Non-linear mapping displays were generated for each of ten different feature sets that had yielded high accuracy training recognition. Initially, each

NLM procedure was limited to 1000 iterations. Any cells which were observed to fall in a cluster of cells of different class for most feature sets were re-classified for a subsequent re-training procedure. The results of this operation conducted with 1000-iteration NLM displays were previously listed in Table 9. The subsequent prediction results for the 1990 data were listed in Table 10. The same 1000-iteration NLM-based re-classification/ training/prediction procedure was also conducted with the class-weighted training method for the 1989-1990 data, and the results were reported earlier in Tables 13 and 14.

To evaluate the validity of the NLM-based reclassification/re-training procedure, additional NLM displays were generated for the same feature sets using 3000, 5000, and 8000 iterations. For class-weighted training, NLM displays did not show any significant changes in the identification of anomalous cells, despite changes in the displays themselves, with NLM iterations varying from 1000 to 8000.

For the non-class-weighted training-selected features, NLM displays changed significantly from 1000 to 5000 iterations, with corresponding changes in the cells identified as anomalous. No changes occurred between 5000 and 8000 iterations. Thus, we considered 8000-iteration NLM displays as "stable"; anomalous cells were re-classified based on these displays, followed by re-training and prediction. The results are listed in Tables 23 and 24. Only two cells were re-classified (Nos. 247, 267, changed from class 3 to class 1). Training accuracy improved to 95.2% overall, with 100% recognition of both class 1 and class 2 cells (compared to 88.1, 100, and 88.1% accuracy, respectively, before re-classification/re-training, Table 9). Prediction results improved to

73.8% overall (compared to 61.9%, Table 10). Class 1 prediction ability did not change significantly (58.3%, 3 false positives, 7 of 10 selections correct) when compared to 50%, 2 false positives, 6 of 8 selections correct, (Table 10), whereas, class 2 prediction improved considerably to 76.9%, 2 false positives (compared to 69.2%, 7 false positives, Table 10).

It is important to observe that re-classification/re-training and subsequent prediction results may be affected by NLM mapping errors. Moreover, it appears that both training and prediction accuracies are generally improved by increasing NLM iterations to the point where "stable" displays are used for identifying and re-classifying anomalous cells. This appears to be less crucial with class-weighted training features.

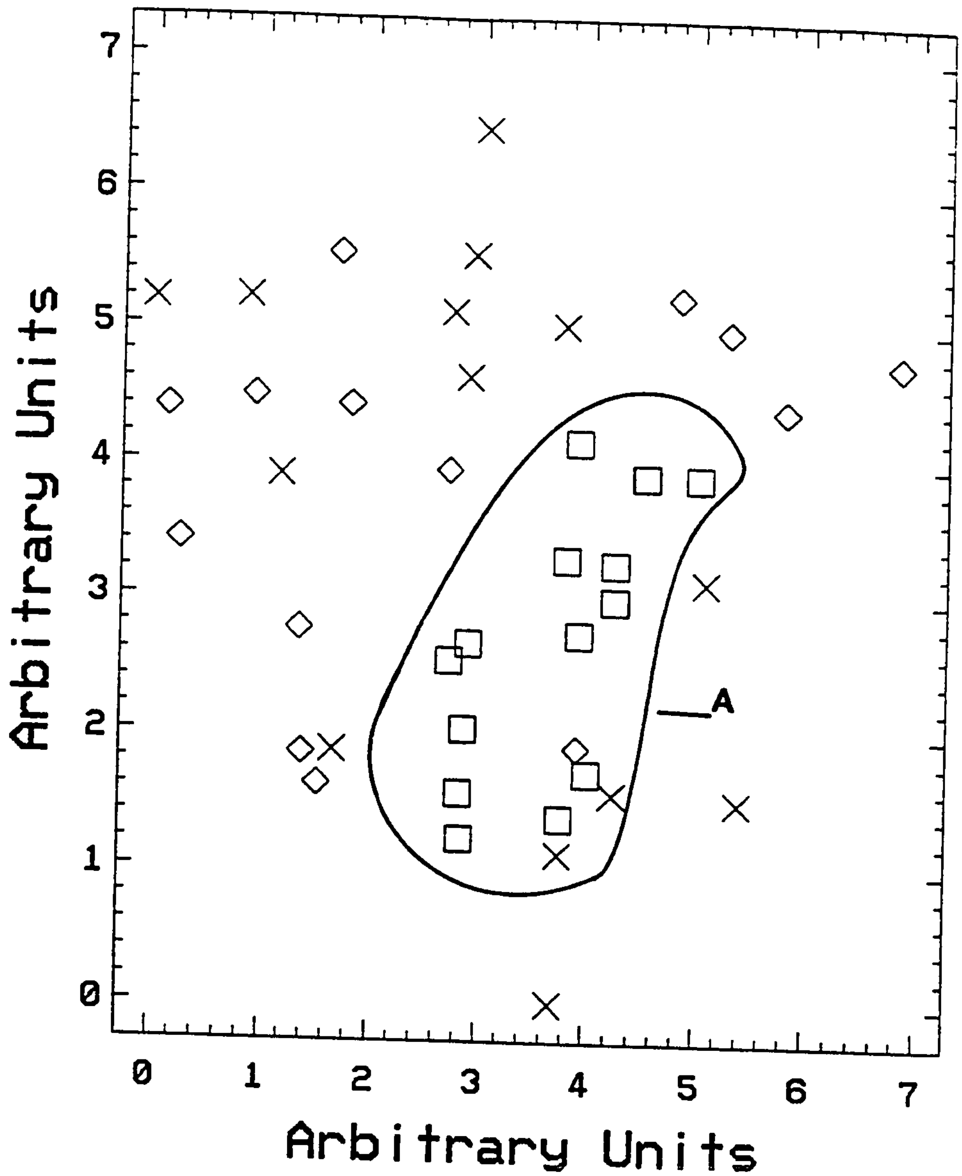


Figure 12. Non-linear mapping (NLM) of GNB cell fabrication and maintenance features. Maintenance data collected at CEMC prior to March, 1989, capacity test. The iteration number is 1000 and successful features: AVSA, NCLV1/3, DRYWT (2). □ = High-capacity cells (class 1) ◆ = low-capacity cells (class 2) × = intermediate-capacity cells (class 3).

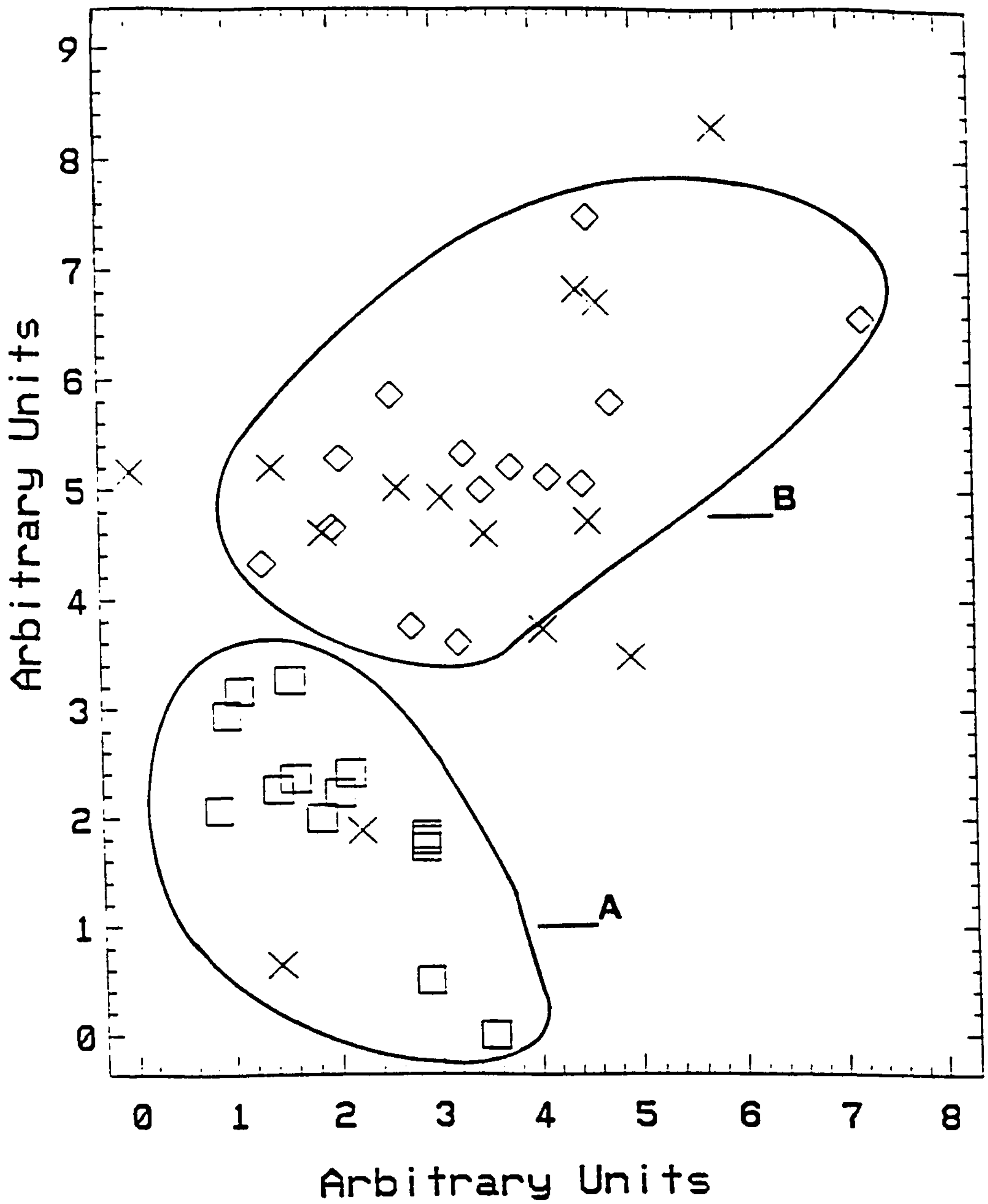


Figure 13. Non-linear mapping (NLM) of GNB cell fabrication and maintenance features. Maintenance data collected at CEMC prior to March, 1989, capacity test. The iteration number is 8000 and successful features: AVSA, NCLV1/3, DRYWT (2). □ = High-capacity cells (class 1) ◆ = low-capacity cells (class 2) × = intermediate-capacity cells (class 3).

Table 23

Combination data training best results for 3-class after NLM (8000 iterative cycles) re-classification.

Maintenance data collected prior to March, 1989, capacity test[a].

% Classification Accuracy Overall/ Class1/ Class2/ Class3	Feature Used (weights)
95.2 / 100 / 100 / 83.3	NCLV1/3(2), LEVEL(T-2), EQWF(2), DRYWT
95.2 / 100 / 92.9 / 91.7	NLVL1/2, DRYWT(2), PVLT, NCLV1/3, SHPLFA

[a] Total patterns: 42, Class 1 = high-capacity cells (14), Class 2 = low-capacity cells(14), and Class 3 = intermediate-capacity cells (14).

Table 24

Combination data prediction best results for 3-class after NLM (8000 iterative cycles) re-classification.

Maintenance data collected prior to April, 1990, capacity test[a].

Auto scaling[b]	FP[c] Cls1	Cls2	% Classification Accuracy Overall/ Class1/ Class2/ Class3	Feature Used (weights)
J	3	10	42.9 / 58.3 / 30.8 / 41.2	EQWC, SHPLFA, NSG1/4, AVGVLT, NCLV1/3
J	6	2	61.9 / 91.7 / 38.5 / 58.2	NLVL1/2, AVSA, DRYWT, MXCAP
I or J	6	2	73.8 / 91.7 / 76.9 / 58.8	AVGLVL, SHPLAF(2), AVSB, NLVL1/2, DRYWT(2), MXSA, MXCAP, AVSA(2)

[a] Total patterns: 42, Class 1 = high-capacity cells (12), Class 2 = low-capacity cells (13), Class 3 = intermediate-capacity cells (17).

[b] Two options: Joint or individual autoscaling. Selecting "J" (JOINT), training and prediction sets scaled together; selecting "I" (INDIVIDUAL), training set autoscaled as a block; then, uses average and standard deviation from training set to autoscale each prediction pattern.

[c] FP = false positive

3.8. Discussion

This study represents a significant step towards achieving practical implementation of pattern recognition performance prediction methods for individual cells in large energy storage batteries. Several procedures were investigated here for the first time: class-weighted training/prediction; combination of fabrication and maintenance data; and optimized NLM-based cell re-classification/re-training procedures. In addition, this was the first study to examine the training and prediction results over two complete two-year cycles (1989-90, 1990-91).

The class-specific prediction results are very encouraging, particularly for predicting poor performing cells. The 1990 prediction results indicate that as many as 11 of 13 class 2 cells could be pre-selected with only 3 false positives; the 1991 prediction results indicate that 10 of 16 class 2 cells could be pre-selected, but with 6 false positives. Pre-selection of high performance cells is also approaching practical levels. The 1990 prediction results for one feature set indicate 6 of 8 cells selected were correctly identified as class 1, whereas 1991 results for one feature set indicate that 7 of 11 cells selected were correctly identified as class 1.

With regard to practical implementation of the procedures described here for realistic pre-selection of high-performance and low-performance cells, several factors must be considered. These are discussed below.

One concern is that training procedures produce several different high accuracy feature sets, only some of which provide high accuracy prediction. How does one determine in advance which feature sets are going to provide accurate classification of unknown cells? This work suggests that NLM displays of alternative feature sets from training will allow selection of the most useful sets for prediction based on visual observation of cluster separations (e.g., compare Figures 12 and 13).

Another important factor is the quality of battery maintenance data collected. It was observed previously [2,29] that water addition measurements were obviously useful features for multivariate analysis, but these have not always been obtained reliably. In fact, one outcome of these studies has been to place additional emphasis on the maintenance data collection effort.

One additional, more subtle, factor to consider is the objective of cell pre-selection. If a few high-performance cells are to be selected for a specific demanding application, it may be satisfactory to identify only some of the high-performance cells, as long as there are no false positives. On the other hand, if the objective is to arrange all available cells into separate strings with matching cell capacities, high overall prediction accuracy is the most desirable. Finally, if poor performing cells are to be pre-selected and removed from operation to prevent the occurrence of cell reversals or catastrophic failures, the highest possible accuracy for identifying class 2 cells is desired, even if a few false positives are involved; the falsely identified cells might be replaced unnecessarily, but their replacement would cause no harm to the system.

One important observation to come out of these studies is which features are most useful for class recognition. Considering the frequency with which a given feature appears in the individual feature sets yielding the most accurate prediction results as an indication of usefulness, the following features were notable:

Most Frequent	Frequent
Class 1: MXCAP	DRYWT, SHPLFA, MXSA, AVSA, NLVL2/1
Class 2: MXCAP, AVSA, DRYWT	MXSA, SHPLFA, NLVL2/1

Many other features are also useful as can be seen from surveying all the tables summarizing prediction results in the body of this report. However, it is interesting that the same set of features appear most frequently for accurate class-specific prediction of both classes, with some differences in their weighting. It is also very interesting to observe that nearly all of the most useful features come from the fabrication data (compare above list in Tables 1 and 6). This is the strong confirmation of observations made in earlier multivariate analysis studies [2, 27, 28] that lead-acid battery fabrication data contain information predictive of battery properties well into the lifetime of the battery.

Chapter 4

CONCLUSION

The results of this work have brought us much closer to the goal of providing a practical pattern-recognition based procedure for anticipating individual cell performance for large energy storage battery systems. The added dimension of class-weighted training investigated in this work is particularly useful because of the class-specific cell recognition objectives which might be a part of any practical application. In addition, it is clear that pattern recognition accuracy with combined fabrication and maintenance data is significantly improved over that obtained previously with each type of data individually [29,30]. It is certainly clear that performance-predictive information is contained in both data sets.

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